

Problem-Driven Design Studies
--Money Donation to Public
School



By Huaying Tian & Arthur Sun

OUTLINE



What are we going to do?



What are we going to do with the data?



Why do we need visualization?



What data do we abstract?



How to visualize the data?

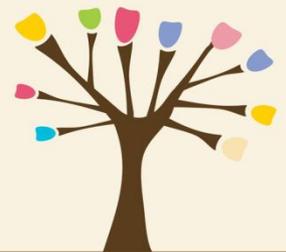
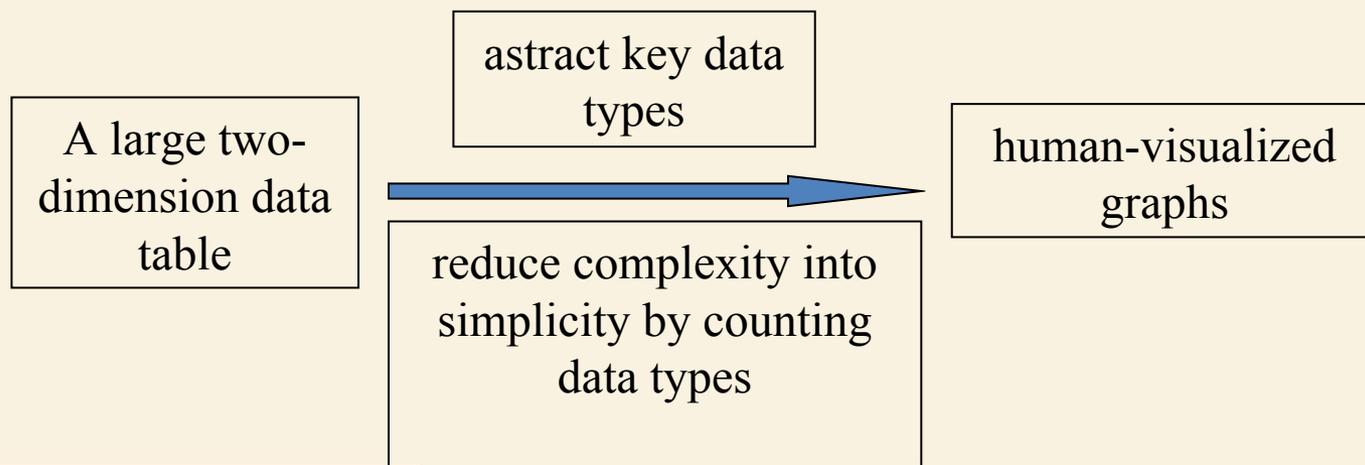


Components of our analysis and function

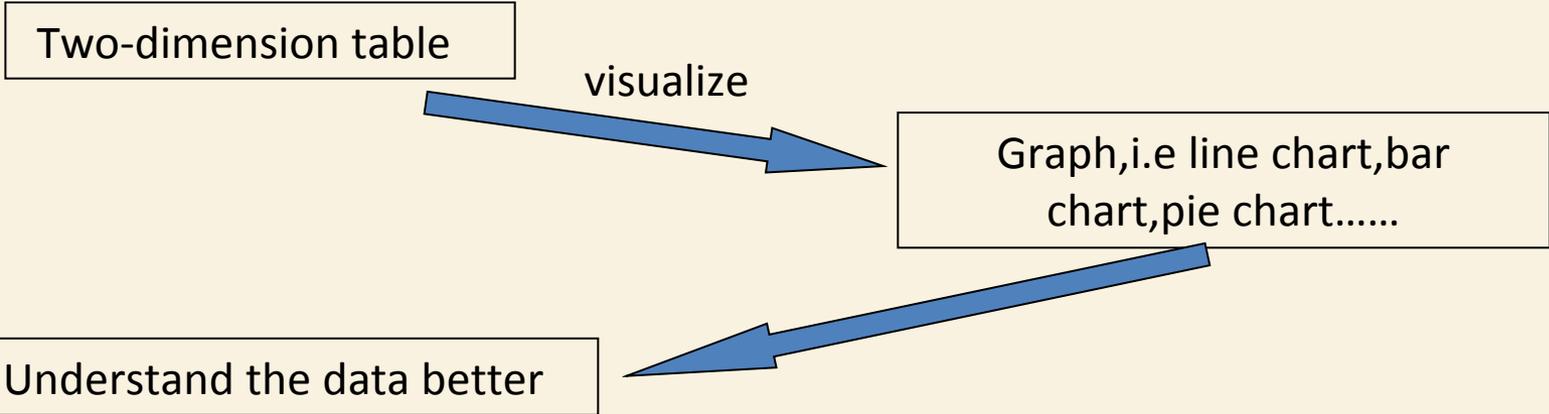


What are we going to do?

1. Analyze data from a US based non-profit organization website that allows individuals to donate money directly to public school ;
2. Get the dataset and take a 9000-row table subset of the original dataset for our analysis purposes;
3. Create an informative analysis on the basis of the data attributes;
4. Visualize the data in an efficient and expressive way.



What are we going to do with the data?



Purpose: Analyze the data better and give appropriate suggestions on public donation

1. What is the trend of number of donations in recent years? Do we need more donations or the status quo is just what we want?
2. Which state shall we pay more attention to?



Why do we need visualization?

Through a problem-driven process, these specialized datasets are often an interesting mix of complex combinations of and special cases of the basic data types, and they also are a mix of original and derived data.

Without vis, we may see a table like that:



	A	B	C	D	E	F	G	H	I	J	K	
1	projectid	teacher_acctid	schoolid	school_nc	school_la	school_lc	school_ci	school_state	school_zi	school_mes	school_district	school_coun
2	"e565fb42185c6e"	"2e17c8c91cb58132d810c"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
3	"76108ed46f99f2"	"6b3721c9585633fa716e"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
4	"2568882e490684"	"ed55d66251be5810b38e"	"923a1f4850d4e09ad5b8d03.60E+11	40.74221	-74.002	New York	NY		10011	urban	New York City Dept	New York (M
5	"e49f6d07f9da70"	"ba7ada7b8ef61280b6e8f"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
6	"548b161b4e808f"	"58574f5ee5f3d74a4be1"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
7	"dfc5e3a3bd22d8"	"fedc7312fac70db43893"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
8	"be3c6a88818ef6"	"2e6deb2edcb9b2ef9bf4"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
9	"dd7ed1d74f70fb"	"d8f151a88a6d298fe5e6"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
10	"c5d4a7877c463e"	"262af4de8528628259ac"	"8c9ab8c021074381647582e1115072"	40.82696	-73.8922	BRONX	NY		10459			Bronx
11	"8d94b233b50e7f"	"f8e7fa9cc031249fa674"	"15b661612d21c9dd37de0092ed81e00"	40.82696	-73.8922	Bronx	NY		10459			Bronx
12	"8b19da4400111a"	"760f8b3ac86e3ac286c6e"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
13	"4f93f03be059a8"	"e5d28482308e2007992ae"	"9bc7d4d92193a453669b6e3.60E+11	40.70178	-74.0118	New York	NY		10004	urban	Other	New York (M
14	"eef82859f1dd50"	"8fb8a281a46527b9e7ea"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
15	"f38c2d5f55f407"	"964aa5f2734897fbd99ac"	"eab5debe9b88fbb9b15fe13.60E+11	40.78333	-73.9459	New York	NY		10128	urban	New York City Dept	New York (M
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17	"17466db6d83288"	"dab65ac402878a610353"	"1ae4695be589a36816188e3.60E+11	40.76552	-73.9601	New York	NY		10065		New York City Dept	New York (M
18	"f4a27a5e375c9a"	"5955995b38eba124a51b"	"5c5c444dd1bf31c3bdbcf43.60E+11	40.76825	-73.989	New York	NY		10019	urban	Empowerment Support	New York (M
19	"52b04391f8e028"	"ded4b1235dbdaedeb157"	"8c9ab8c021074381647582e1115072"	40.82696	-73.8922	BRONX	NY		10459			Bronx
20	"c97b3d603e4999"	"263a93c35a3a52ea19abc"	"cb1ac51c57e5ecb8f9a5ak3.60E+11	40.68683	-73.9808	Brooklyn	NY		11217	urban	New York City Dept	Kings (Brool
21	"0cab719d819193"	"2e17c8c91cb58132d810c"	"45e7ddbddd7023f1eb65a6c3.60E+11	40.84169	-73.8755	Bronx	NY		10460	urban	New York City Dept	Bronx
22	"57d68f35b13a19"	"f7fada7c19ac859803c3"	"38ada3531c8f57cab78b0418bbc03e4"	40.64959	-73.9583	Brooklyn	NY		11226		New York City Dept	Kings (Brool
23	"b24064984f054b"	"067ca75f07e29bc8daf2"	"8c9ab8c021074381647582e1115072"	40.82696	-73.8922	BRONX	NY		10459			Bronx
24	"9a3f66830e2112"	"d1d684f1549f4e5b9693"	"ec26adc6baee71abbcebf73.60E+11	40.72369	-73.9816	New York	NY		10009	urban	New York City Dept	New York (M
25	"d1cfcfa7e85ba9"	"fff493aaf228cd88040df"	"756e5d578f2c6482c287bc3.60E+11	40.68494	-73.9473	Brooklyn	NY		11216	urban	New York City Dept	Kings (Brool
26	"9a6f4fb43bf27e"	"5d11379c28c7a4103287c"	"60d87aa721f3a17c0628913.60E+11	40.83826	-73.8661	Bronx	NY		10460	urban	New York City Dept	Bronx
27	"8aa59963a2a959"	"ded4b1235dbdaedeb157"	"8c9ab8c021074381647582e1115072"	40.82696	-73.8922	BRONX	NY		10459			Bronx

What a great mass!

But by using visualization, People can have a **clear overview** at first with low-latency page loading of data, and then zoom and filter to check the **details** they demand



What data do we abstract?

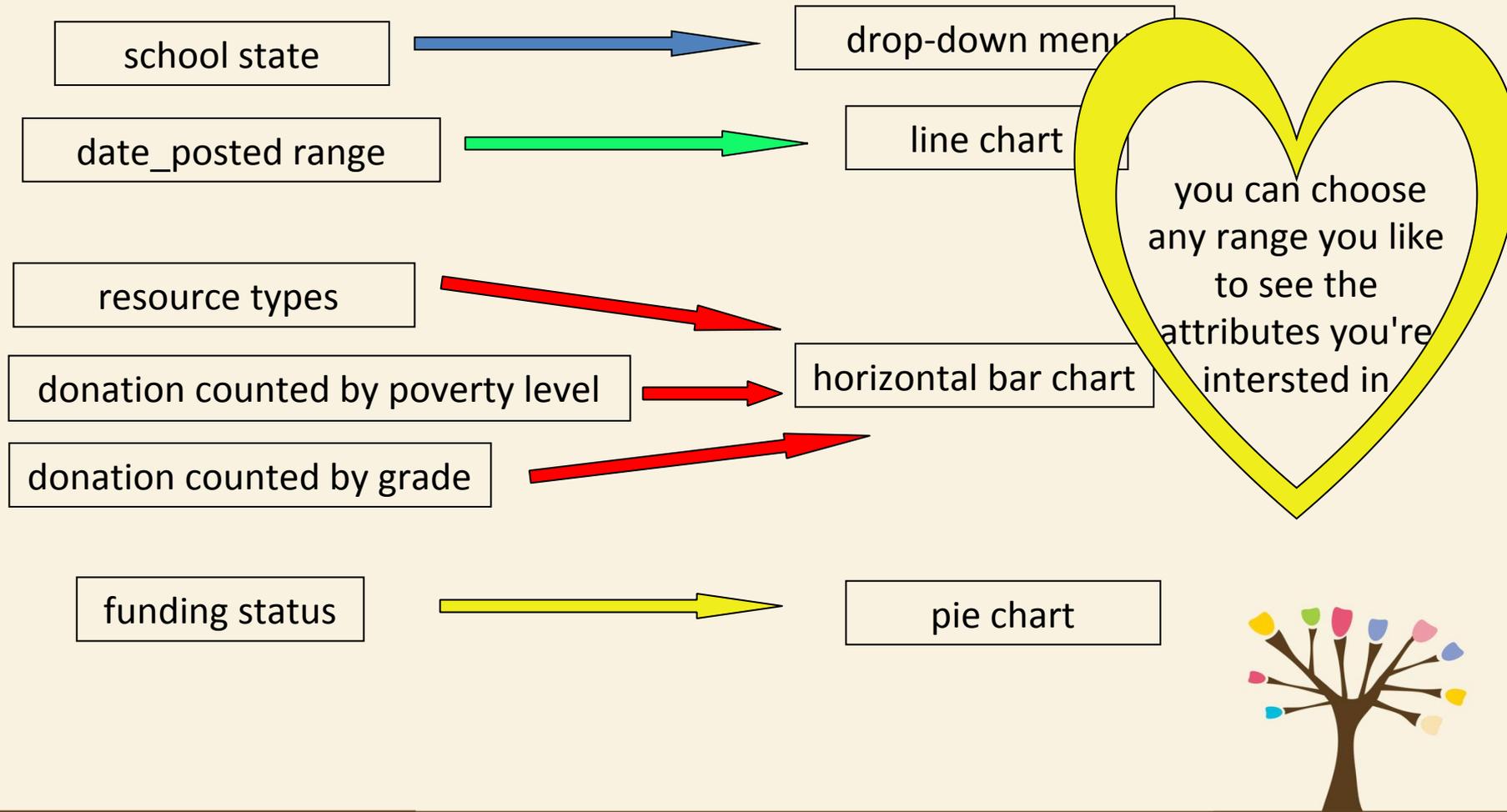
Data types:

1. school_state: NY,NC or.....
2. resource_type: books ,technologies,or.....
3. poverty_level: Highest poverty ,low poverty or.....
4. date_posted: day,month,year
5. total_donations: how much donations they've received
6. funding_status: completed or expired
7. grade_level 9-12,5-8 or



How to visualize the data?

Data Visualization:



The components of our analysis and their function

1.D3.js: A javascript based visualization engine which will render interactive charts and graphs based on the data.

2.Node JS: Our powerful server which serves data to the visualization engine and also hosts the webpages and javascript libraries.

3.Mongo DB: The resident No-SQL database which will serve as a fantastic data repository for our project.



Thanks



Students Migration

Elementary and Secondary Schools in São Paulo/Brazil

Carolina Roman Amigo & Wenqiang (Dylan) Dong

CPSC 547 – Information Visualization

October 2015

About the Data

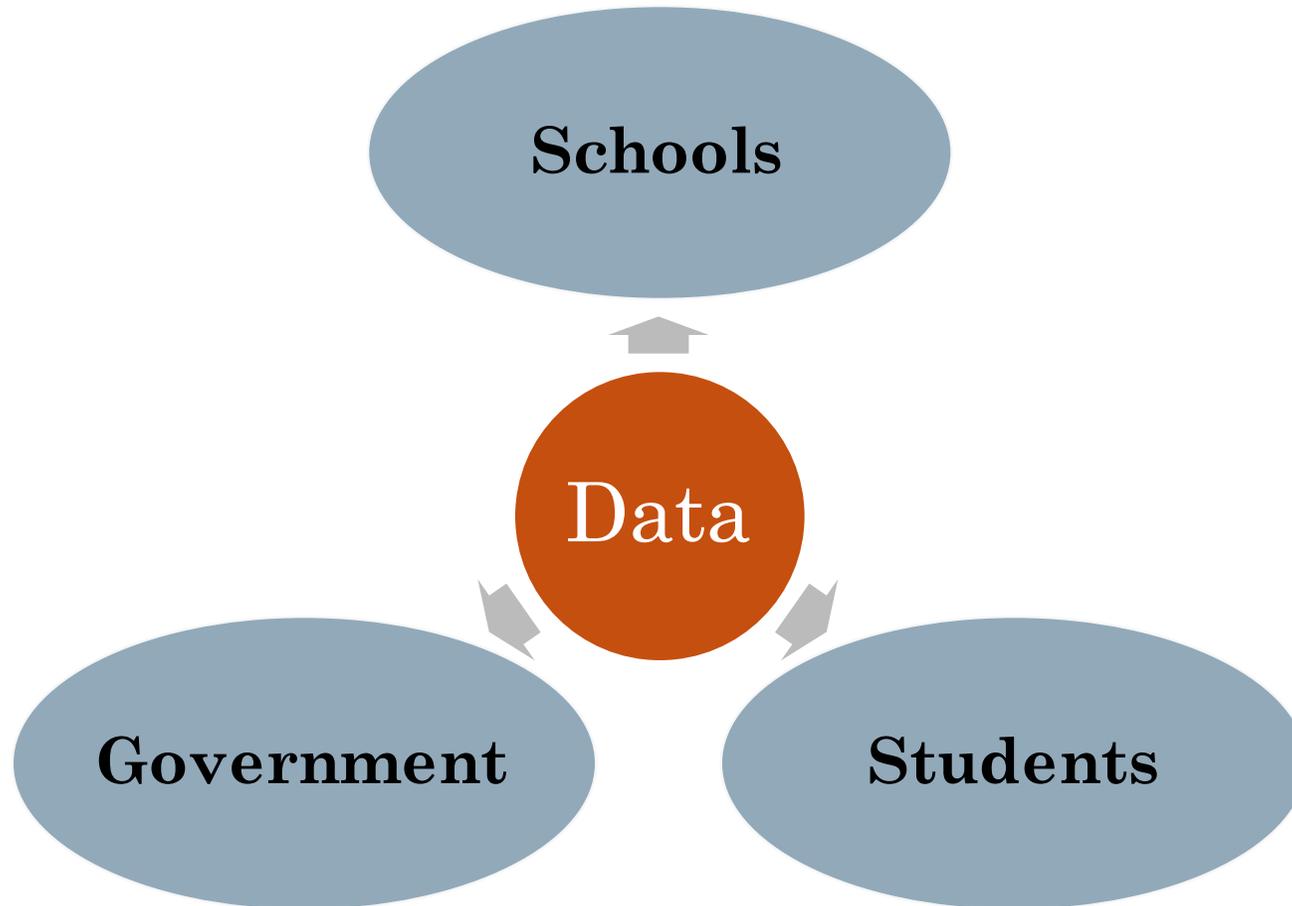
- Educational Census (public available, per year)
 - School code
 - School name
 - School type (private/public)
 - School location (Latitude, Longitude, Postal Code, City, District)
 - Census Year
 - Student Code
 - Student Grade
- Data size (per census year, we need at least two)
 - 7.789.831 Students
 - 20.029 Schools
 - ~ 650 MB

Challenge

Context

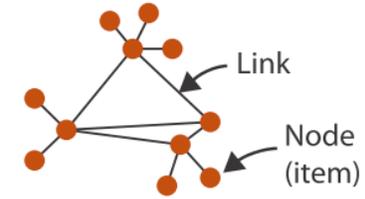
- In Brazil, elementary and secondary public education generally has poor quality.
- Every parent that can afford a private school does it, thus we have a huge number of private schools competing for students.
- They run like businesses, so understanding their market share is relevant for them.
- There is an standardized test for being accepted at the best universities, and some private schools specialize in training students for that; so when getting to high school some students opt for migrating to this kind of schools.

Stakeholders



T1 - Tasks for Schools

- Help schools identify migration pattern of students.
 - Are they losing more students than gaining?
 - To which schools are they going?
 - Is there any particular grade in which migration is more intense?
 - How their students migration compares to the other schools?



T2 - Tasks for Government

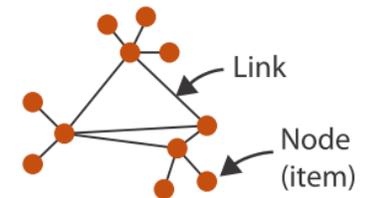
- Are there any areas of the state receiving more students than others?
- Are students migrating from public to private schools?

→ Dataset Types

→ Geometry (Spatial)



→ Networks



T1 - Help schools identify migration pattern of students

- map: school types



categorical color map

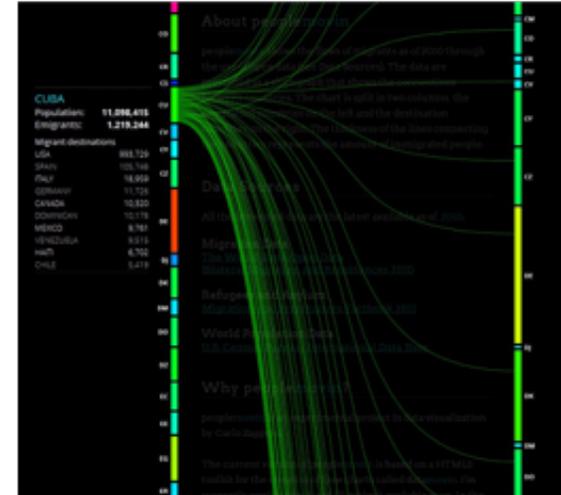


of incoming & outgoing students



line thickness

- interaction: select
- facet: juxtapose



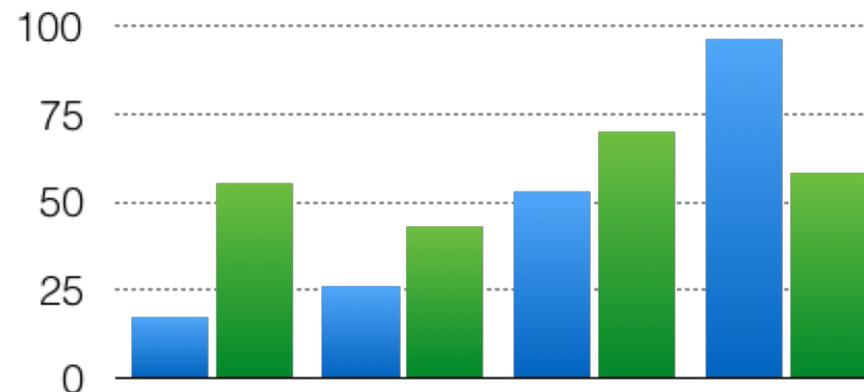
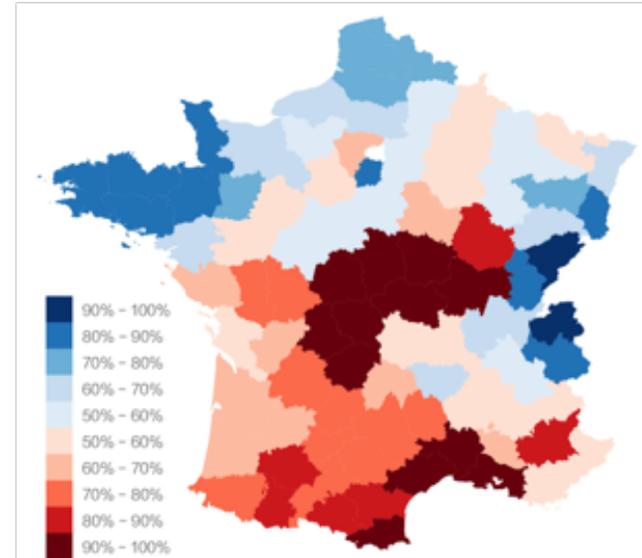
T2 - Which areas of the state are receiving more students?

- map: (incoming-outgoing)%

diverging color map



- interaction: select
- facet: juxtapose



Thank you!

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Wenqiang (Dylan) Dong

wdong@cs.ubc.ca

VISUALIZATION OF YOUTUBE COMMENTS



if I run this throu
you how to do add
makes it look old.

iPhone correct? Might want to try stop
a point and shoot digital. Best Buy has so
or under \$300!!!

Blue & Green color com
2 hrs · Unlike · 1

Yeah, the posing isn't quite
I'm hosting a seminar where you can
re advanced posing techniques next
just head over to my website at.....

1
would never
those flowers to snoot in front of. D
eyes. I've definitely done better.

some of the flaws in MS Paint, no ne
Photoshop. You also need to remen
of 3rds when shooting. That would h
for a much better photo. There are p
videos to help you out on You-Tube
1 hr · Like

You should
help you improv

How come its gotta be a white
racist!
2 hrs · Unlike · 2

NICE DOF DUMBASS

It would look
the outside black
keep her shoes colored. Also
that shot with Janel Jackson a
behind her holding her breast
neat. But she should smile ar
because your model looks re
2 hrs · Unlike · 2

your watermark is distracting
white. you should do it like me...
letters in the bottom corner of every
worry... nobody on the iternet will
em
2

Omg Nino Bat
dited those limbs from it
s leg. I can't believe you
ion like that

fancy camera makes. You
long way with your hobby,
2 hrs · Unlike · 2

you really just obj
can you live with
hoo haa..... (shar
www.

A little tip on posing.. H
and middle finger are to close together
ems she had webbed alien hands. I have
Get this snapshot outta here
posed to shoot outsi

I know you are already finishe
with this but....

- Doesn't support easy finding of entertaining comments.
- Emotionally draining arguments and trolls.

- Doesn't support easy finding of entertaining comments.

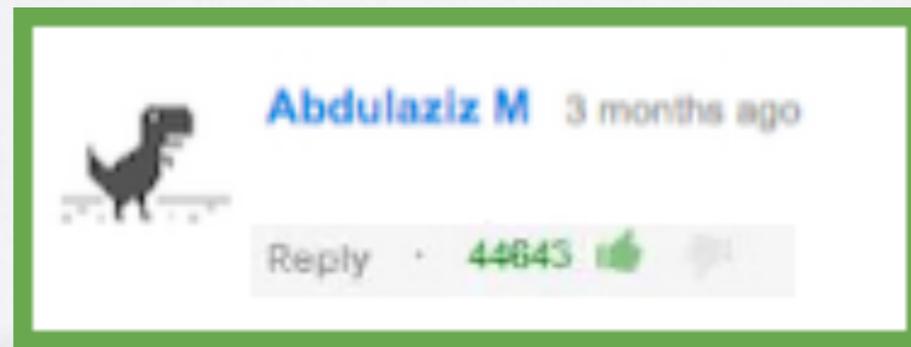
Task 1: Explore for entertaining comments.

- Emotionally draining arguments and trolls.

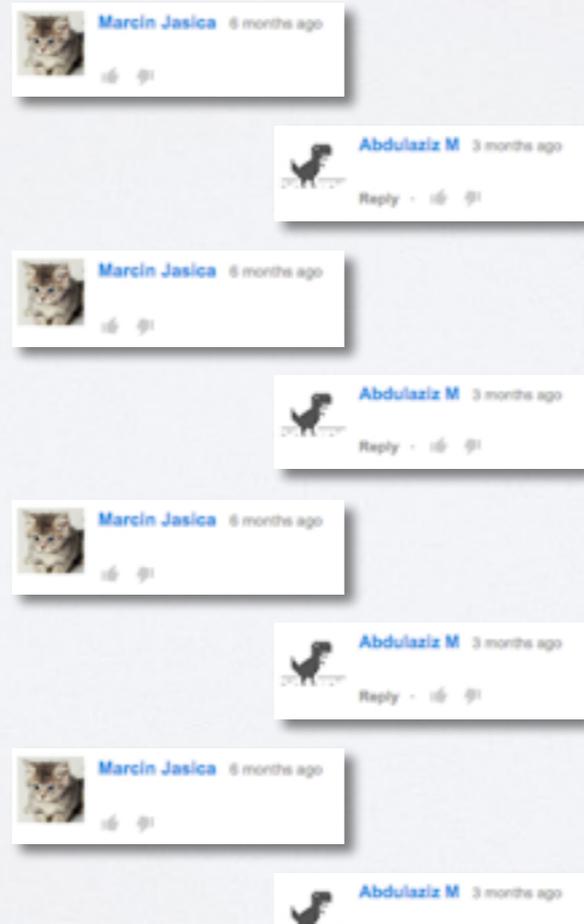
Task 2: Identify arguments.

Task 3: Identify trolls.

- Entertaining comments = highly liked comments (generally)



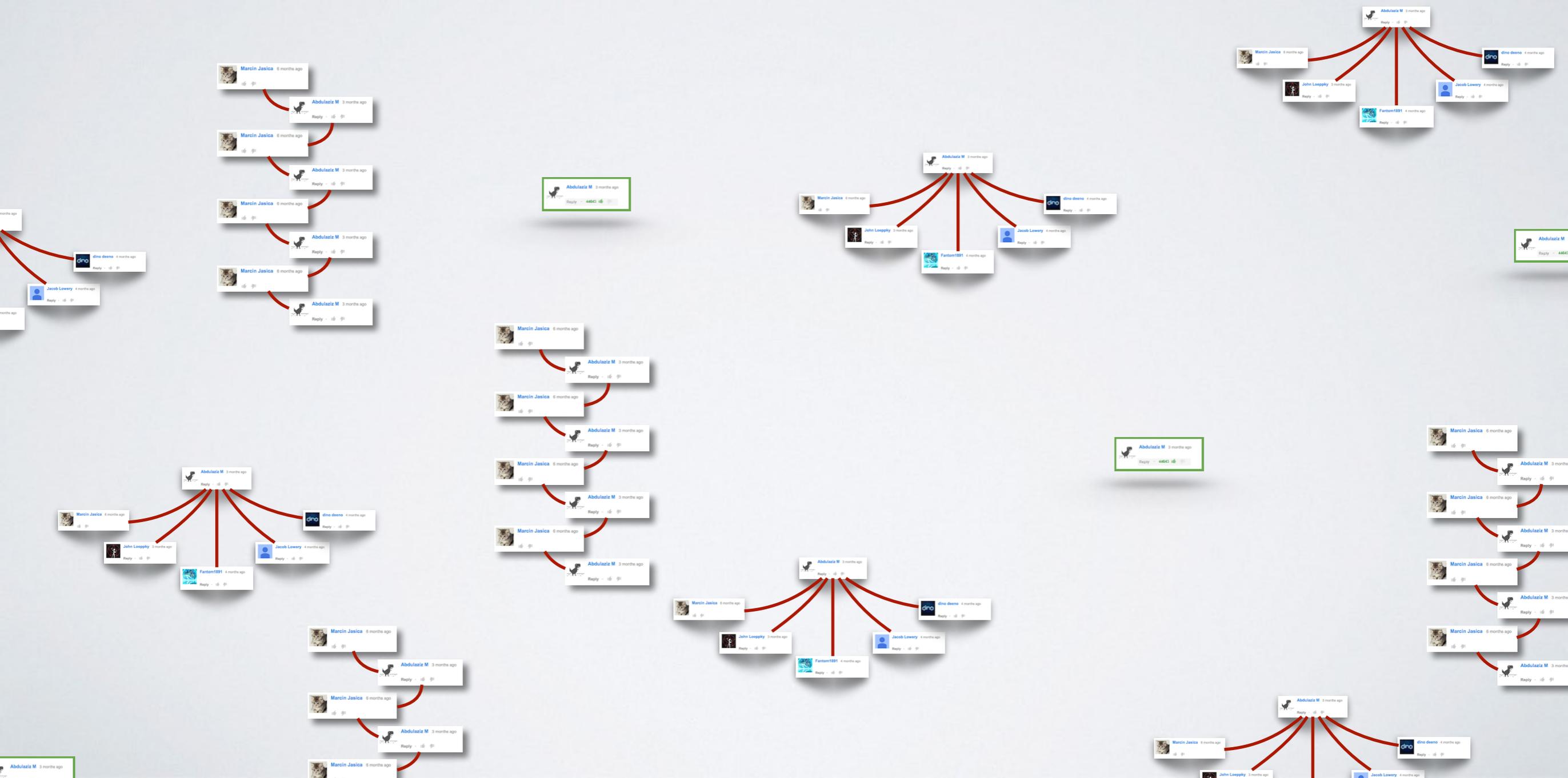
- Arguments = Long back-and-forth between two users with little or no likes



- Trolls = A single user (with little or no likes) being bombarded by multiple users



Idea: A Bird's Eye View of the Youtube Comment Section



Neuron electrophysiology data visualization (Neuroelectro)

Presented by: Dmitry, Emily and Mike

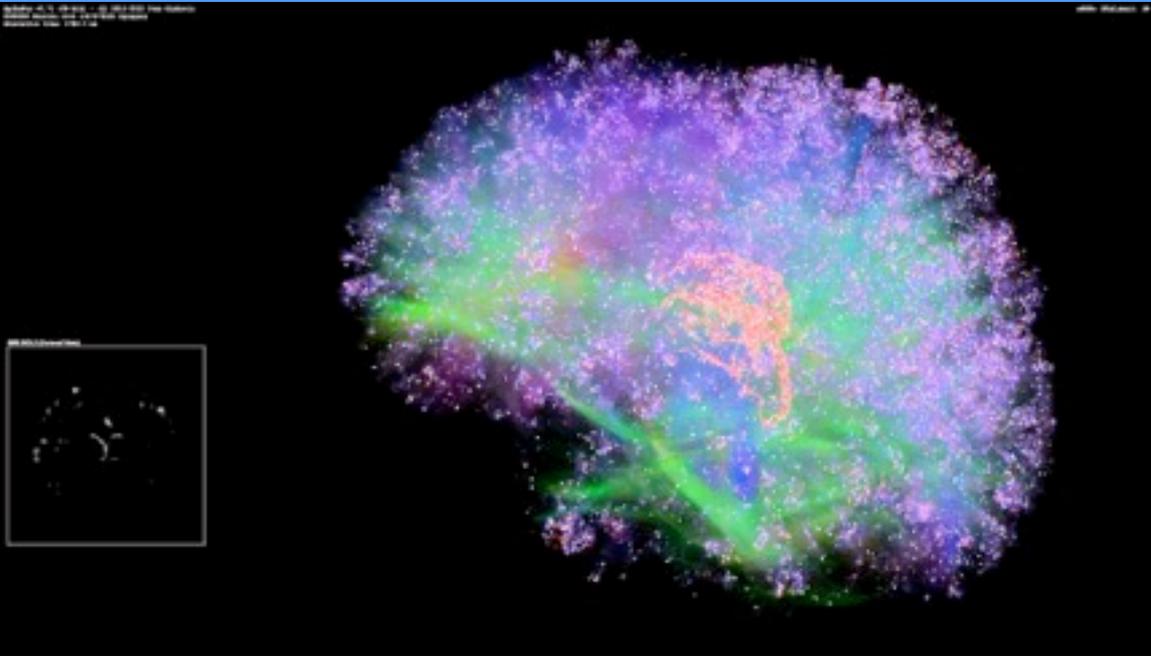


Introduction

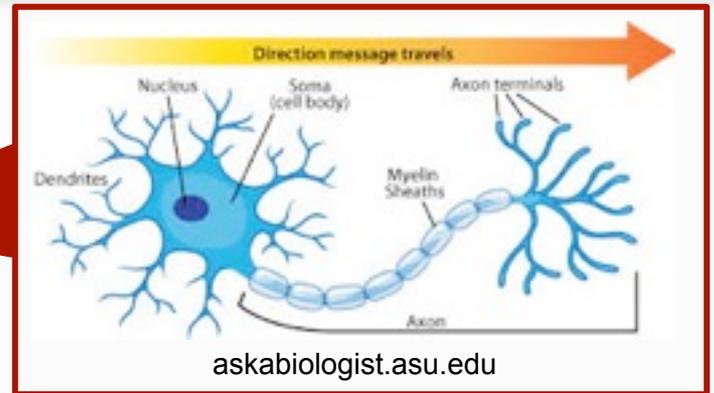
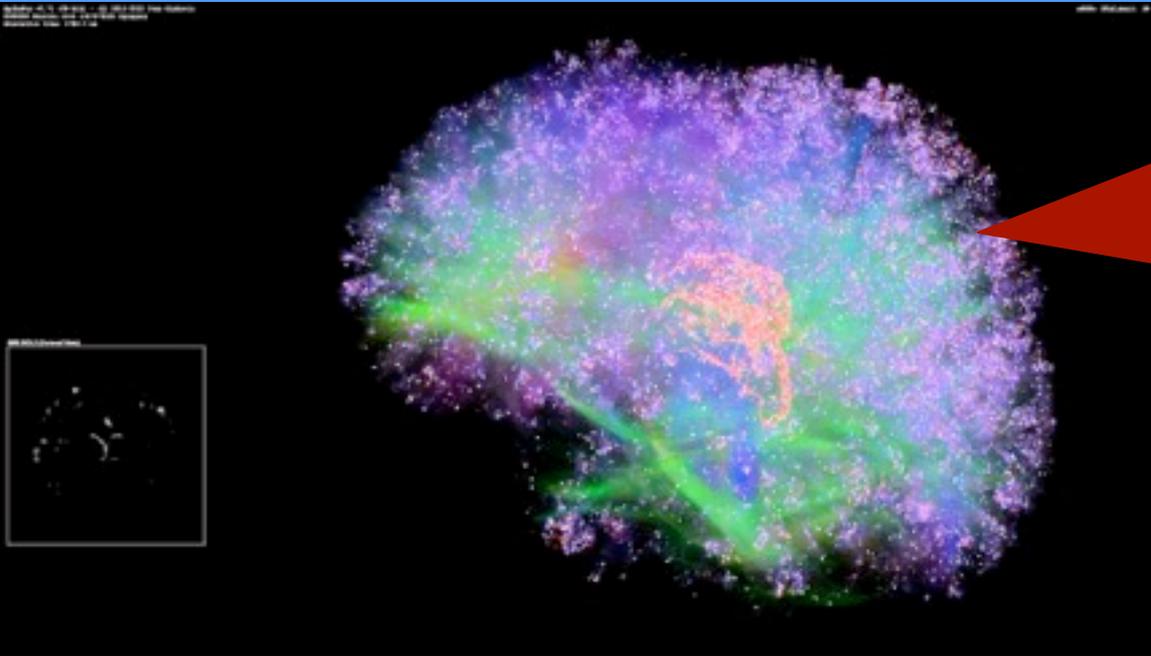
Dmitri



How does your brain work? It's complicated



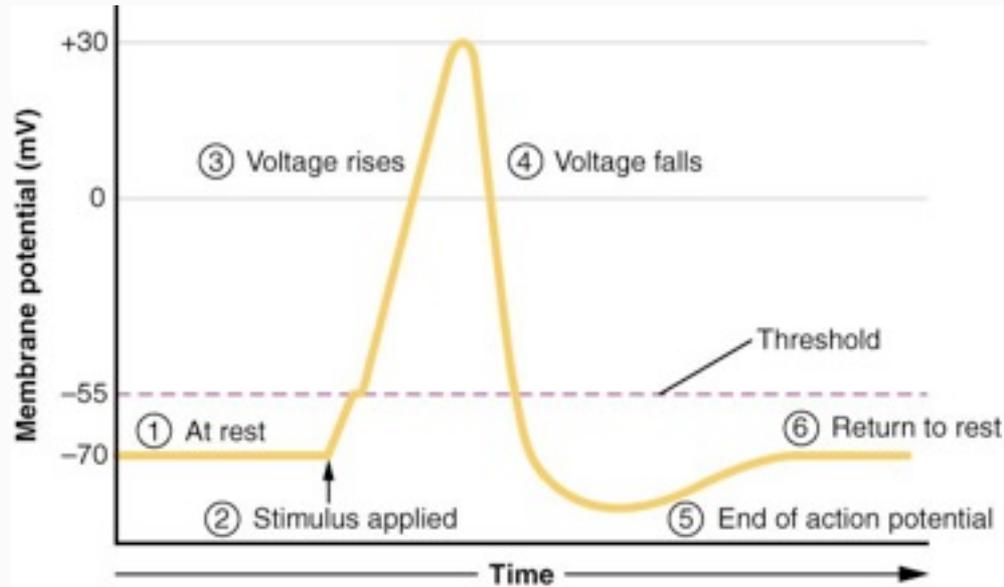
How does your brain work? It's complicated



What is our data?

Electrophysiology is the study of the electrical properties of biological [cells](#) and [tissues](#). In [neuroscience](#), it includes measurements of the electrical activity of [neurons](#), and particularly [action potential](#) activity.

-wikipedia



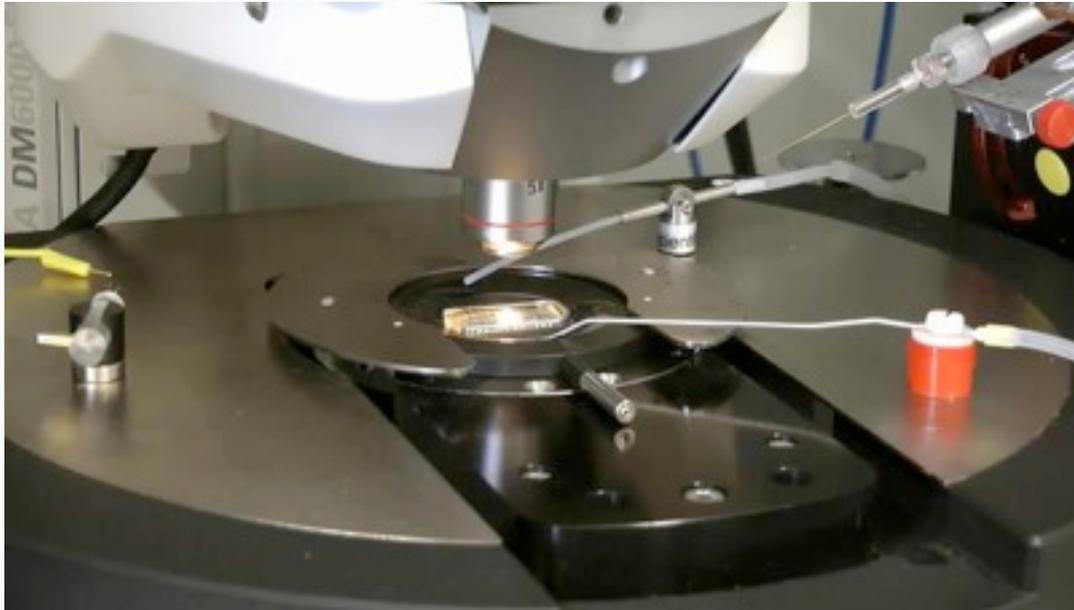
What is our data?

How many neuron types are there? The debate has been ongoing for decades. We use enhanced NeuroLex.org definitions (~100 Neuron types)



What is our data?

Experimental metadata - solutions used, temperature, electrode types, animal species, strain and age, etc.



What is our data?



To summarize we have (per article):

- 1) Electrophysiology properties
- 2) Neuron types
- 3) Experimental metadata

We extract all of the above from published articles through text-mining and curation.

Current State

Mike



NeuroElectro: organizing information on cellular neurophysiology.

The goal of the NeuroElectro Project is to extract information about the electrophysiological properties (e.g. [resting membrane potentials](#) and [membrane time constants](#)) of diverse neuron types from the existing literature and place it into a centralized database.

Published literature

Novel subcellular distribution pattern of A-type K⁺ channels on neuronal surface.
 Unique clustering of A-type potassium channels on different cell types of the main olfactory bulb.

Kudo M, Yokoyama H, Arita M, Nishio J.
 Biophysical and functional studies predicted a highly non-uniform distribution of voltage-gated ion channels on the neuronal surface. This was confirmed by novel immunolocalization experiments for Na⁺, Ca²⁺, and hyperpolarization-activated mixed cation and K⁺ channels. These experiments also indicated that some K⁺ channels were clustered in synaptic or non-synaptic membrane specializations. Here we analyzed the subcellular distribution of Kv4.2 and Kv4.3 subunits in the rat main olfactory bulb at high resolution to address whether clustering characteristics, their distribution, and whether they are concentrated in synaptic or non-synaptic junctions. The cell surface distribution of the Kv4.2 and Kv4.3 subunits is highly non-uniform. Strong Kv4.2 subunit immunopositive clusters were detected in intercellular junctions made by mitral, external plexiform and granule cells (GC). We also found Kv4.3 subunit immunopositive clusters in periglomerular (PGC), long short axon and GCs. In the periglomerular region some subunit immunopositive glial cells encase neighboring PGC somata in a cap-like manner. Kv4.2 subunit clusters are present in the cap membrane that directly contacts the PGC, but not the one that faces the neuropil. In membrane specializations established by members of the same cell type, K⁺ channels are enriched in both membranes, whereas specializations between different cell types contain a high density of channels asymmetrically. None of the K⁺ channel-rich junctions showed any of the ultrastructural features of known chemical synapses. Our study provides evidence for highly non-uniform subcellular distributions of A-type K⁺ channels and predicts their involvement in novel

Physiology database

Olfactory Bulb Mitral Cell

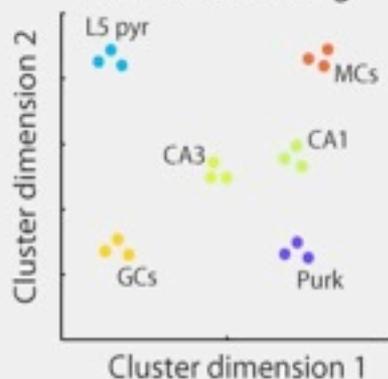
Input resistance	200 MΩ
V _{rest}	-65 mV
Spike width	1 ms
...	

CA1 Pyramidal Cell

Input resistance	400 MΩ
V _{rest}	-70 mV
Spike width	5 ms
...	

Extracted from Literature

Neuron clustering



Our goal is to facilitate the discovery of [neuron-to-neuron relationships](#) and better understand the role of functional diversity across neuron types.

Listing of neuron types in the database

Electrophysiology values across neuron types obtained are obtained from semi-automated literature text-mining.
 (neuron types are mostly from [NeuroLex.org](#))

Show entries

Search:

Neuron type	Number extracted electrophysiology values	Number articles
Other	1119	70
Hippocampus CA1 pyramidal cell	505	66
Dorsal root ganglion cell	353	23
Neocortex pyramidal cell layer 5-6	281	33
Neocortex basket cell	185	25
Neostriatum medium spiny neuron	163	23
Neocortex pyramidal cell layer 2-3	144	19
Neocortex uncharacterized cell	143	12
Dentate gyrus granule cell	107	18
Medial vestibular nucleus neuron	102	7

Showing 1 to 10 of 235 entries

◀ Previous Next ▶

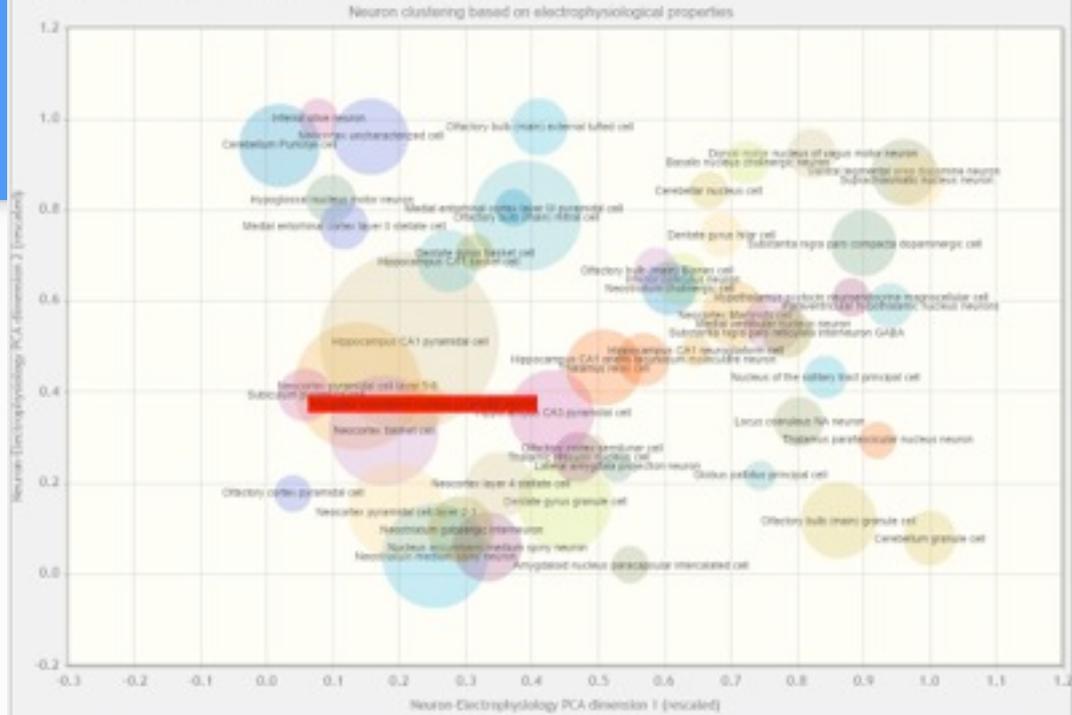
Clustering of neuron types based on similarities in electrophysiological values:

Description:

- Projection of NeuroElectro neuron types onto space defined by the first 2 electrophysiology principal components which collectively represent ~70% of variance. Neuron types are indicated by circles and circle size is proportional to number of corresponding articles indexed in NeuroElectro database.

Interactivity:

- Click on neuron types to go to corresponding neuron page
- Zoom in on a section of plot by dragging cursor. Zoom out by double clicking on plot.



- Show neuron names
- Don't show neuron names

Display a specific neuron(s):

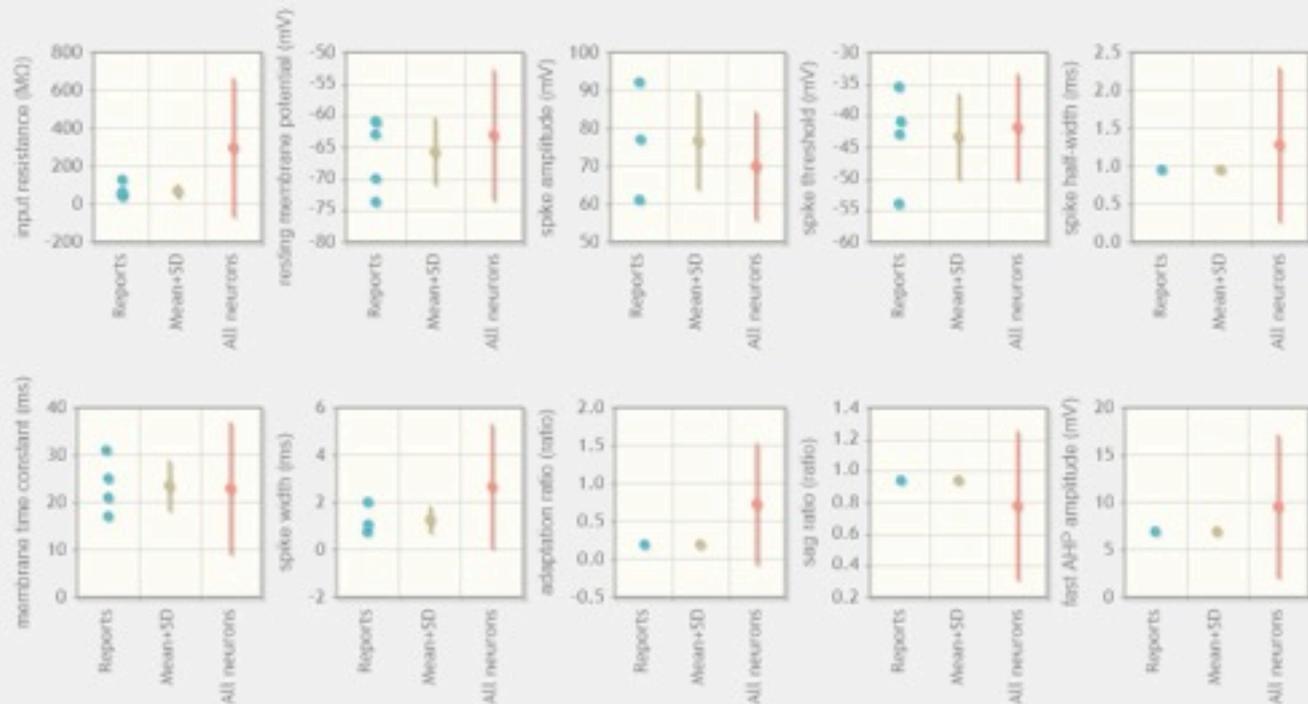
- None selected
- Amgydala basolateral nucleus** ▲
- Amgydala nucleus parvocellular
- Basalis nucleus cholinergic
- Cerebellar nucleus cell
- Cerebellum granule cell ▼

Electrophysiological properties of Amygdala basolateral nucleus pyramidal neurons from literature:

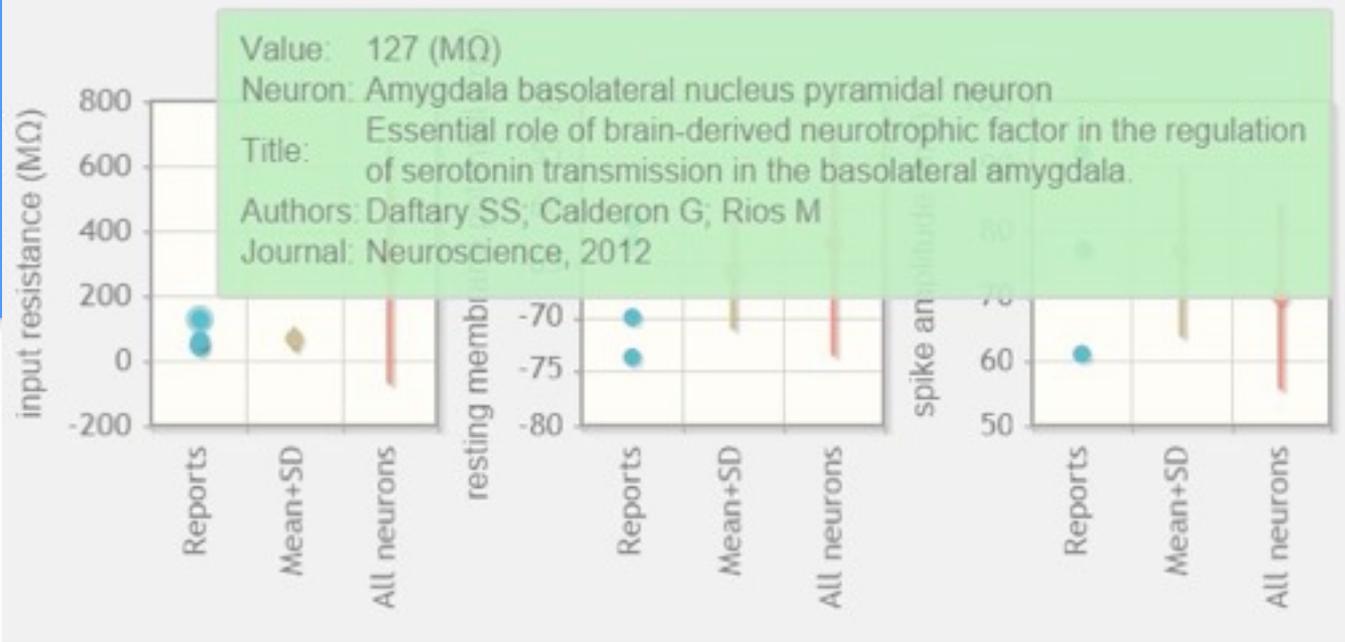
- Legend:
- Reports: Blue dots indicate human-curated values; Orange dots indicate non-human curated values
 - Mean+SD: mean and standard deviation of human-curated neuron measurements
 - All neurons: mean and standard deviation computed over all neurons in database
- Interactivity:
- Mouse over neuron report data points and click to view corresponding publication
 - Mouse over y-axis labels to view definition or click to view values across neuron types
 - Zoom in on a section of plot by dragging cursor. Zoom out by double clicking on plot.
 - Legend: Blue dots = text-mined values human curated, Orange dots = text-mined values not human curated

View data in table form

Report miscurated data

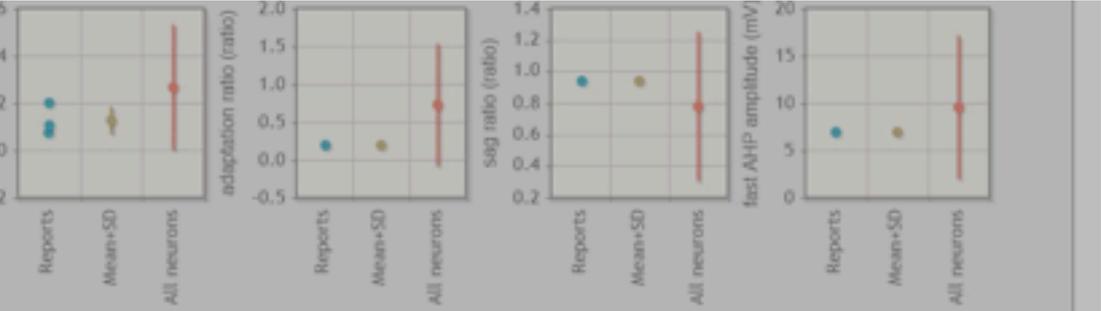
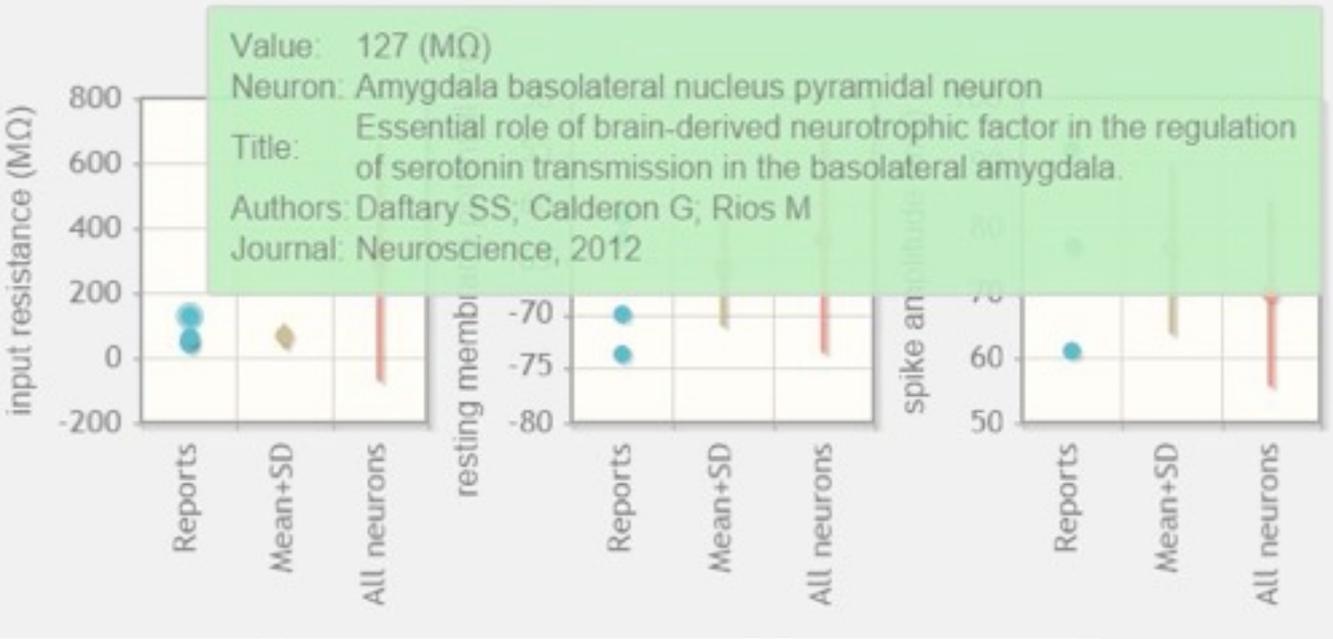
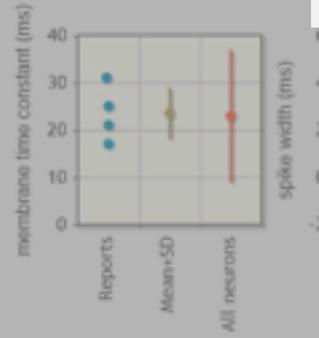
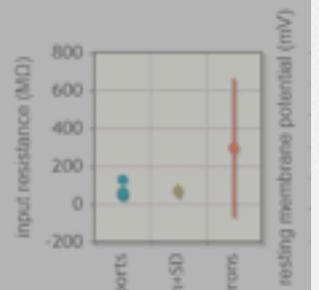


View data in table form



Electrophysiological properties of Amygdala basolateral nucleus pyramidal neurons from literature:

- Legend:
- Reports: Blue dots indicate human-
 - Mean+SD: mean and standard dev
 - All neurons: mean and standard dev
- Interactivity:
- Mouse over neuron report data poin
 - Mouse over y- axis labels to view de
 - Zoom in on a section of plot by drag
 - Legend: Blue dots = text-mined val



View data in table form

Article: Essential role of brain-derived neurotrophic factor in the regulation of serotonin transmission in the basolateral amygdala.

Full Text (publisher's website) ; Article Metadata ; Article Data (extracted)
 Daifany SS, Calderon G, Rios M
 Neuroscience, 2012

Table 1: Physiological properties of BLA pyramidal neurons

Parameter	WT Concept: Amygdala basolateral nucleus pyramidal neuron	BONF2L/2LOL-Cre
Vm (mV) Concept: resting membrane potential	-61±1.2	-63±1.1
Rin (MΩ) Concept: input resistance	127±12	110±10
Tau (ms) Concept: membrane time constant	25±2.3	23±1.8
Spike threshold (mV) Concept: spike threshold	-41±0.6	-40±2.6
Spike amp. (mV) Concept: spike amplitude	77±3.1	77±2.5
Half-spike width (ms) Concept: spike half width	0.95±0.04	1.02±0.05
10-90% rise time (ms) Concept: spike rise time	0.34±0.01	0.37±0.02

Vm, resting membrane potential; Rin, membrane input resistance. No significant difference was observed in the physiological properties of BLA projection neurons from controls and mutants ($p > 0.05$ for all categories).

Report miscurated data

Inferred neuron-electrophysiology data values

Show 50 entries

Search

Neuron Type	Neuron Description	Ephys Prop	Extracted Value	Standardized Value	Content Source
Amygdala basolateral nucleus pyramidal neuron		membrane time constant	25.0 ± 2.3	25.0 (ms)	Data Table
Amygdala basolateral nucleus pyramidal neuron		spike threshold	-41.0 ± 0.6	-41.0 (mV)	Data Table
Amygdala basolateral nucleus pyramidal neuron		spike amplitude	77.0 ± 3.1	77.0 (mV)	Data Table
Amygdala basolateral nucleus pyramidal neuron		spike half width	0.95 ± 0.04	0.95 (ms)	Data Table
Amygdala basolateral nucleus pyramidal neuron		spike rise time	0.34 ± 0.01	0.34 (ms)	Data Table
Amygdala basolateral nucleus pyramidal neuron		resting membrane potential	-61.0 ± 1.2	-61.0 (mV)	Data Table
Amygdala basolateral nucleus pyramidal neuron		input resistance	127.0 ± 12.0	127.0 (MΩ)	Data Table

Showing 1 to 7 of 7 entries

Previous Next

Listing of articles with extracted electrophysiology properties

Article title links out to pubmed abstract

Show entries

Search:

Article Title	Authors	Journal	Year	Electrophys values	Neuron types
Are all spinal segments equal: intrinsic membrane properties of superficial dorsal horn neurons in the developing and mature mouse spinal cord. (NeuroElectro data) (PubMed)	Tadros MA, Harris BM, Anderson WB, Brichta AM, Graham BA, Callister RJ	J. Physiol. (Lond.)	2012	90	1
Morphological and electrophysiological properties of pyramidal-like neurons in the stratum oriens of Cornu ammonis 1 and Cornu ammonis 2 area of Proechimys. (NeuroElectro data) (PubMed)	Scorza CA, Araujo BH, Leite LA, Torres LB, Otalora LF, Oliveira MS, Garrido-Sanabria ER, Cavalheiro EA	Neuroscience	2011	88	3
Target-specific output patterns are predicted by the distribution of regular-spiking and bursting pyramidal neurons in the subiculum. (NeuroElectro data) (PubMed)	Kim Y, Spruston N	Hippocampus	2012	88	2
Hyperexcitability of axotomized and neighboring unaxotomized sensory neurons is reduced days after perineural clonidine at the site of injury. (NeuroElectro data) (PubMed)	Liu B, Eisenach JC	J. Neurophysiol.	2005	78	1
The largest group of superficial neocortical GABAergic interneurons expresses ionotropic serotonin receptors. (NeuroElectro data) (PubMed)	Lee S, Hjering-Leffler J, Zagna E, Fishell G, Rudy B	J. Neurosci.	2010	69	2
Lateral hypothalamic GAD65 neurons are spontaneously firing and distinct from orexin- and melanin-concentrating hormone neurons. (NeuroElectro data) (PubMed)	Kamrani MM, Szabó G, Erdélyi F, Burdakov D	J. Physiol. (Lond.)	2013	56	1
5-HT(3A) receptor-bearing white matter interstitial GABAergic interneurons are functionally integrated into cortical and subcortical networks. (NeuroElectro data) (PubMed)	von Engelhardt J, Khrulev S, Eliava M, Walther S, Monyer H	J. Neurosci.	2011	55	1
Cellular neuroanatomy of rat presubiculum. (NeuroElectro data) (PubMed)	Simonnet J, Eugène E, Cohen I, Miles R, Fricker D	Eur. J. Neurosci.	2013	52	1
Inter- and intralaminar subcircuits of excitatory and inhibitory neurons in layer 6a of the rat barrel cortex. (NeuroElectro data) (PubMed)	Kumar P, Ohana O	J. Neurophysiol.	2008	50	2
Synaptic interactions between pyramidal cells and interneurone subtypes during seizure-like activity in the rat hippocampus. (NeuroElectro data) (PubMed)	Fujiwara-Tsakamoto Y, Isomura Y, Kaneda K, Takada M	J. Physiol. (Lond.)	2004	49	5

Problem Characterization

Emily



Problem Characterization

- We met with our stakeholder to ascertain high-level questions:
 - What do cells in different parts of the brain do?
 - How do experimental conditions affect electrophysiological measurements?
 - etc.
- We refined these into a few abstract tasks...

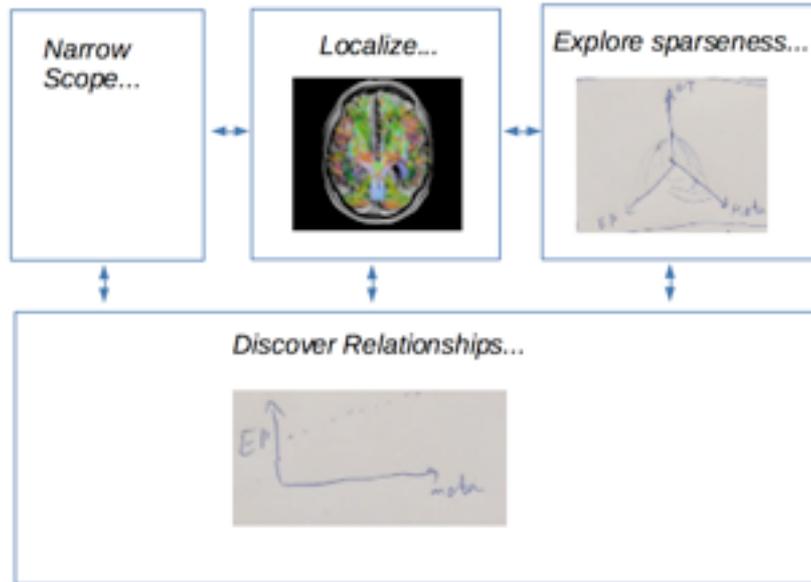
Task Analysis

- *Discover relationships*
 - Neuron types (categorical)
 - Electrophysiological properties (quantitative)
 - Experimental conditions (quantitative and categorical)
- *Narrow scope of analysis*
 - Select experimental conditions and ephys properties to include
 - Filter by neuron type, ephys property, and experimental conditions

Task Analysis

- *Explore* sparseness of data
 - How many data points for each neuron type? property? experimental condition?
- *Localize* neuron types and ephys properties in the brain
- *Lookup* details for individual data points

Tentative Solution



How much time?

Henry

Data Description

- Activity log of my commitments (e.g. CPSC547)
- Only tracks about 40 hours every week
- Categorized by name and project

Task

- Insert text here

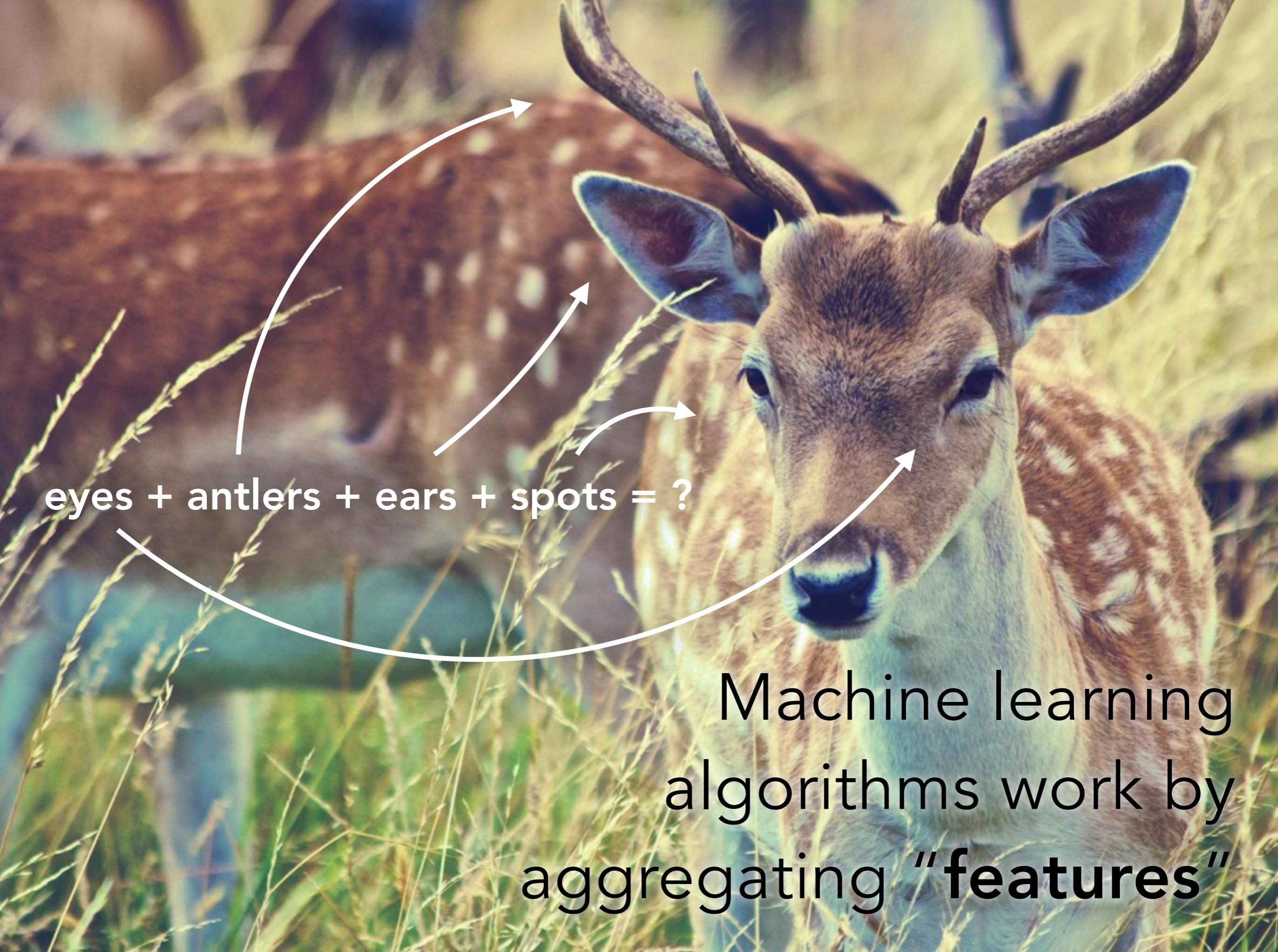
Existing Visualizations

- Calendar
- Pie chart
- Bar chart
- ...

Partner welcome
(no pressure)

VISUALISING FEATURE LEARNING

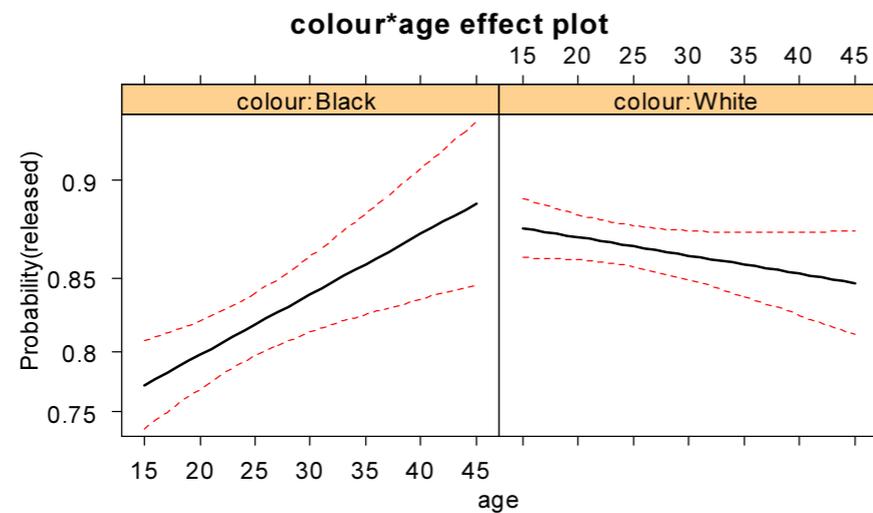
Jason Hartford



eyes + antlers + ears + spots = ?

Machine learning algorithms work by aggregating **“features”**

File Edit View Special



Term	Coefficient	Std. Error	Z Score
Intercept	2.46	0.09	27.60
lcavol	0.68	0.13	5.37
lweight	0.26	0.10	2.75
age	-0.14	0.10	-1.40
lbph	0.21	0.10	2.06
svi	0.31	0.12	2.47
lcp	-0.29	0.15	-1.87
gleason	-0.02	0.15	-0.15
pgg45	0.27	0.15	1.74

To understand features in a model, you used to just look at the fitted parameters

Modern models learn features from data

may have...

100s

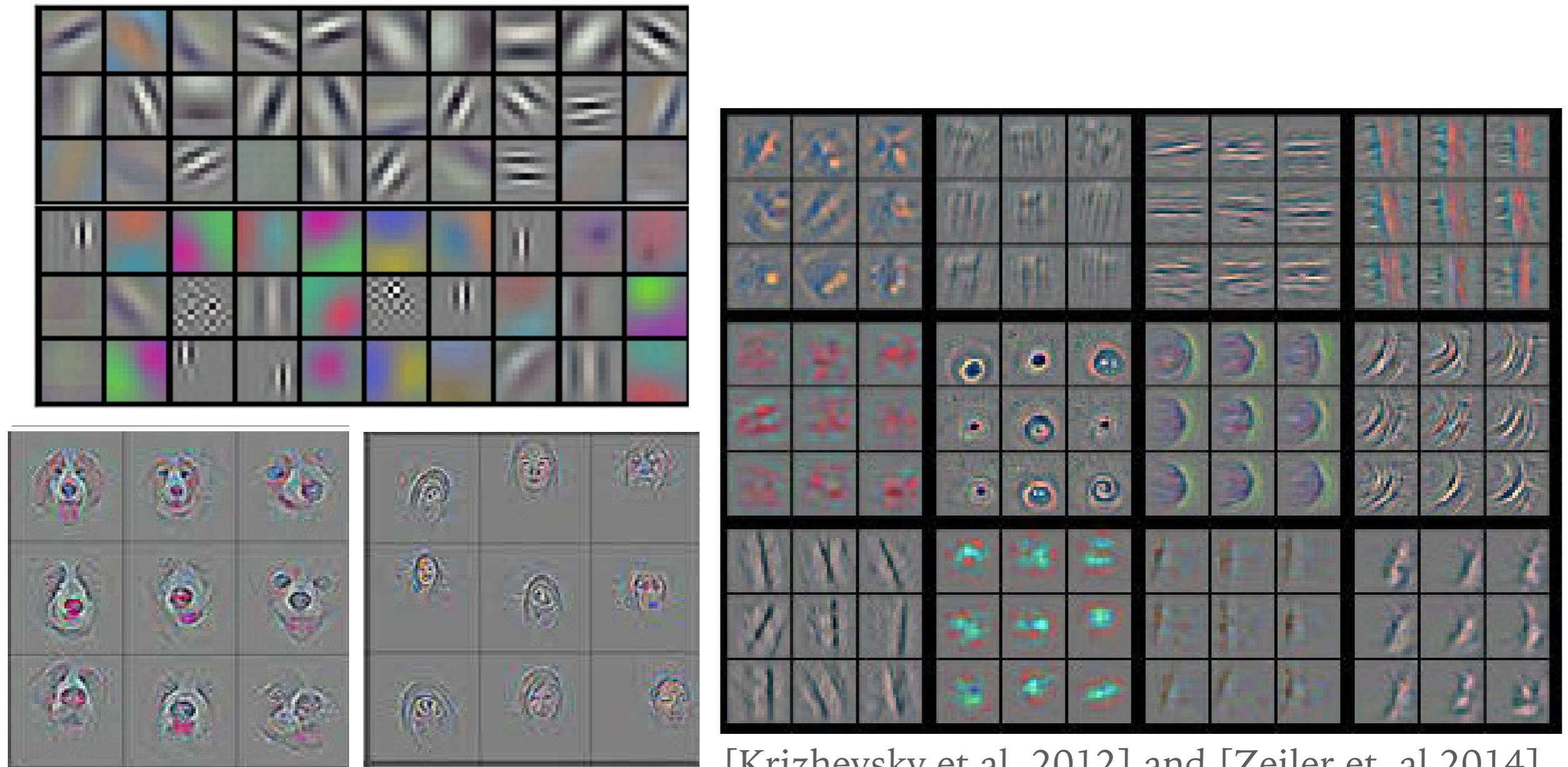
1000s

Millions

of parameters

This makes it very difficult
to understand what's
going on in your model!

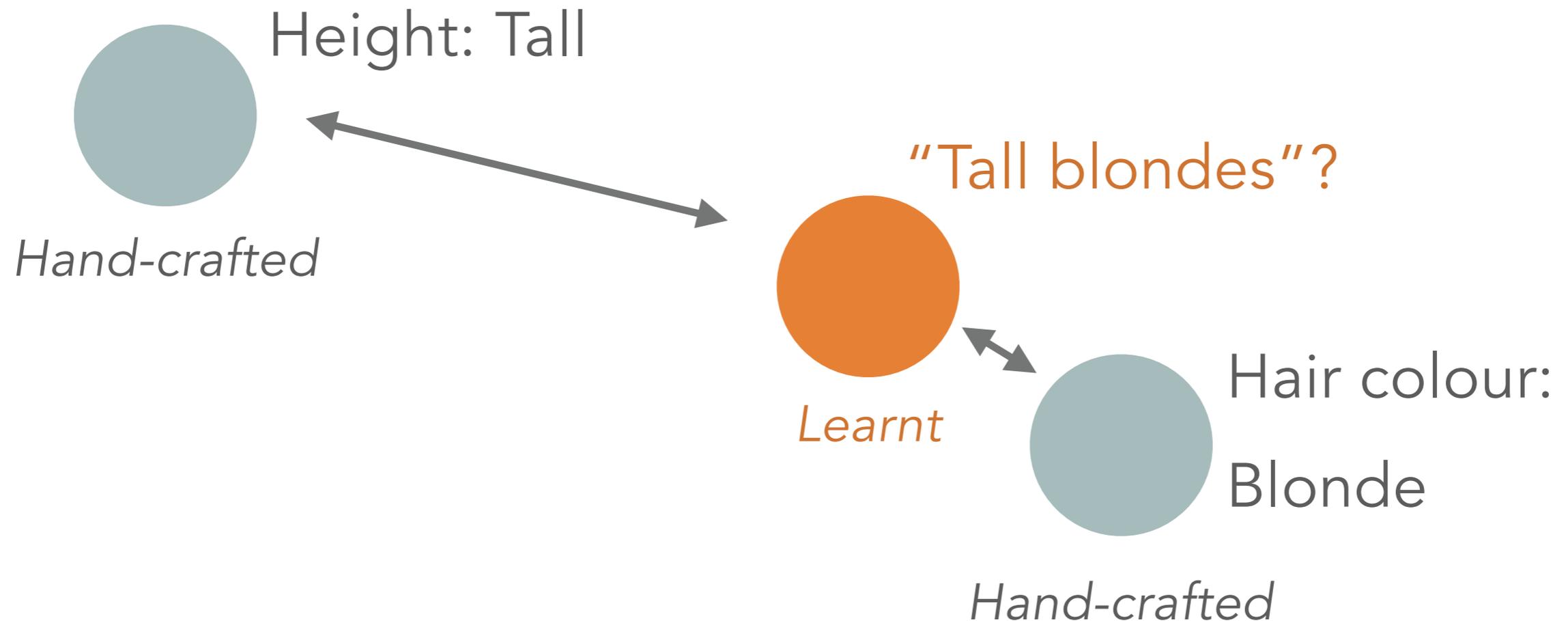
In vision you can plot parameters directly.



[Krizhevsky et al. 2012] and [Zeiler et. al 2014]

... but this only works because of the visual structure of their models.

Feature discovery "*by analogy*"



Idea: derive *distance* between the output of *learnt features* and *hand-crafted features*.

My domain: **Behavioural Game Theory**

understanding human behaviour in

strategic situations



- I have data.

- I have data.
- I have hand-crafted features.

- I have data.
- I have hand-crafted features.
- I have a model.

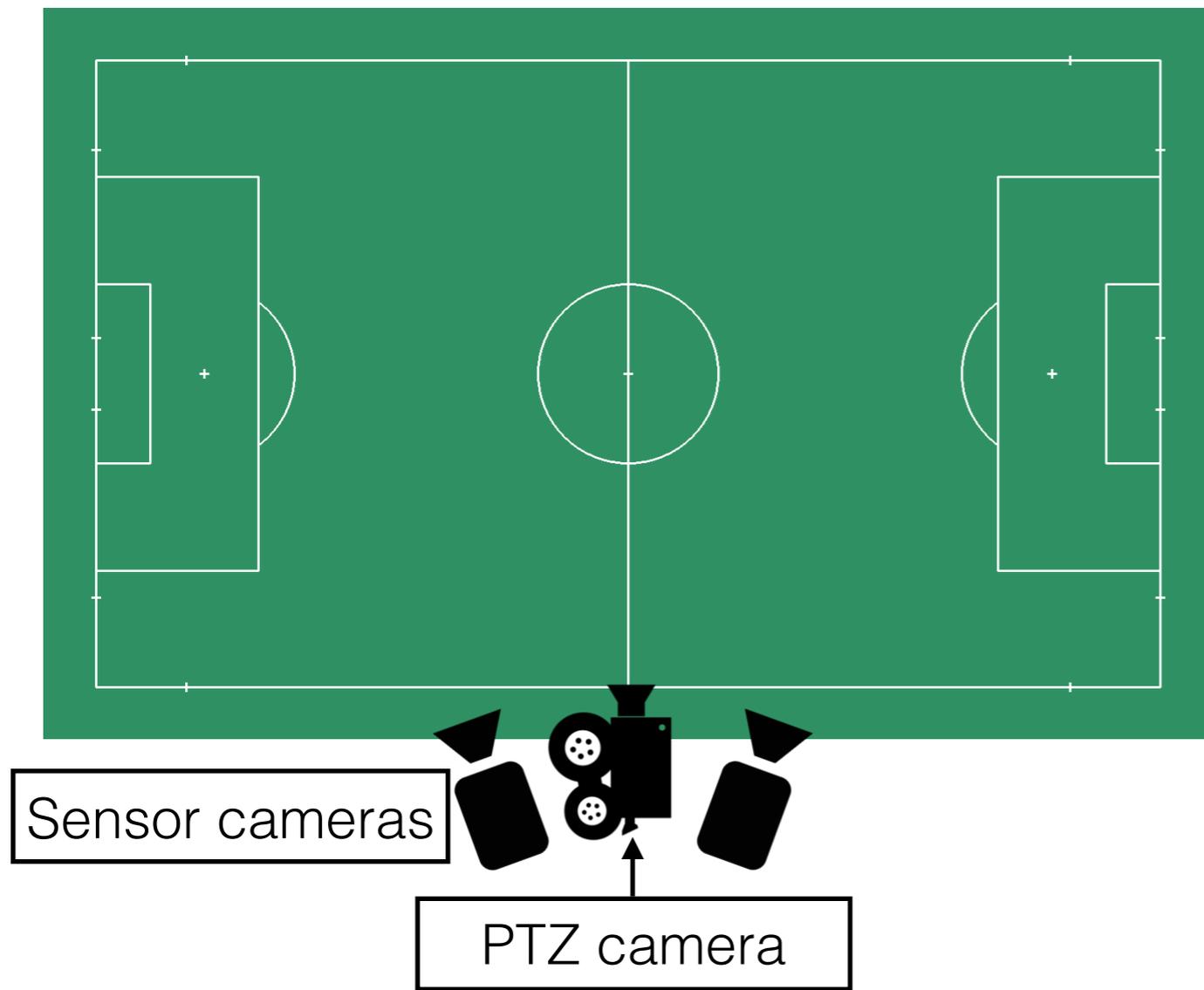
- I have **data**.
- I have **hand-crafted** features.
- I have a **model**.
- I'm not sure what it's learning...

CamermanVis

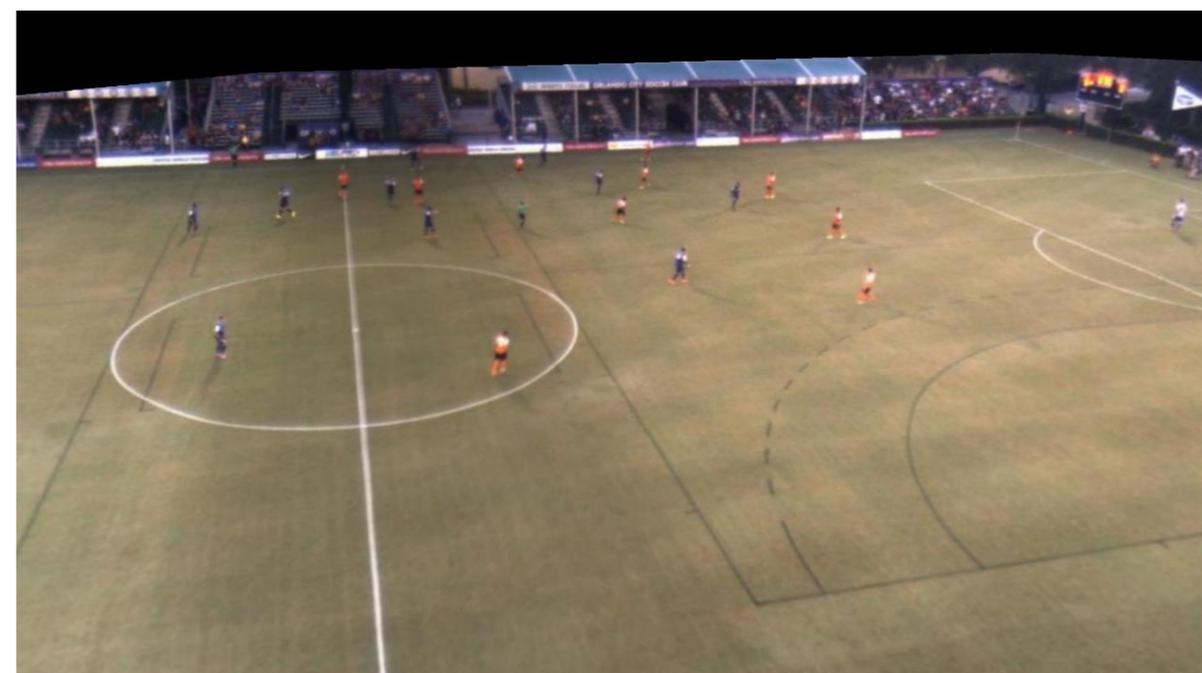
-Where camera should look?

Jianhui (Jimmy) Chen
CPSC 547 Pitch

Cameras for soccer games



Sensor



PTZ

Left or right?



overview

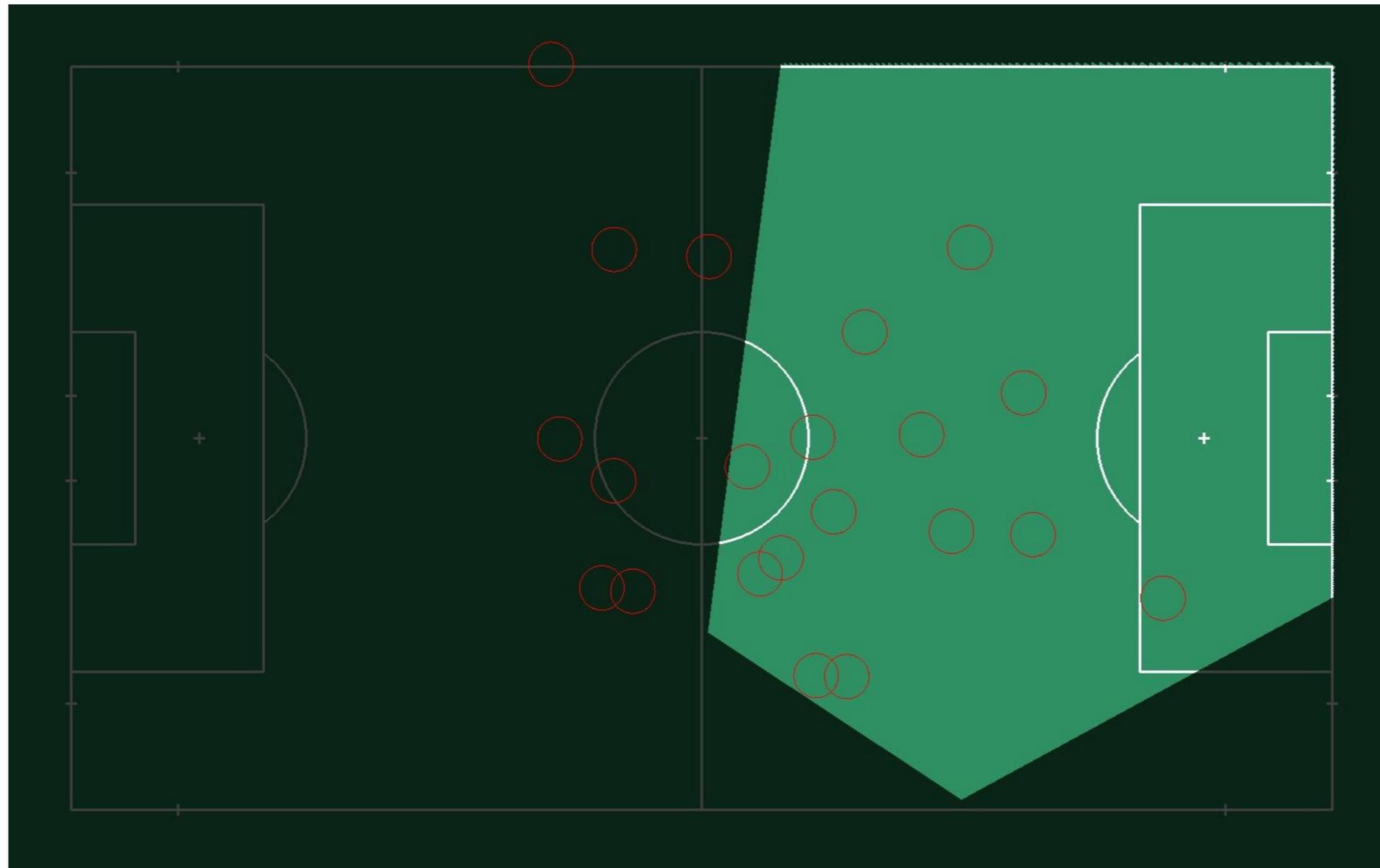


look left

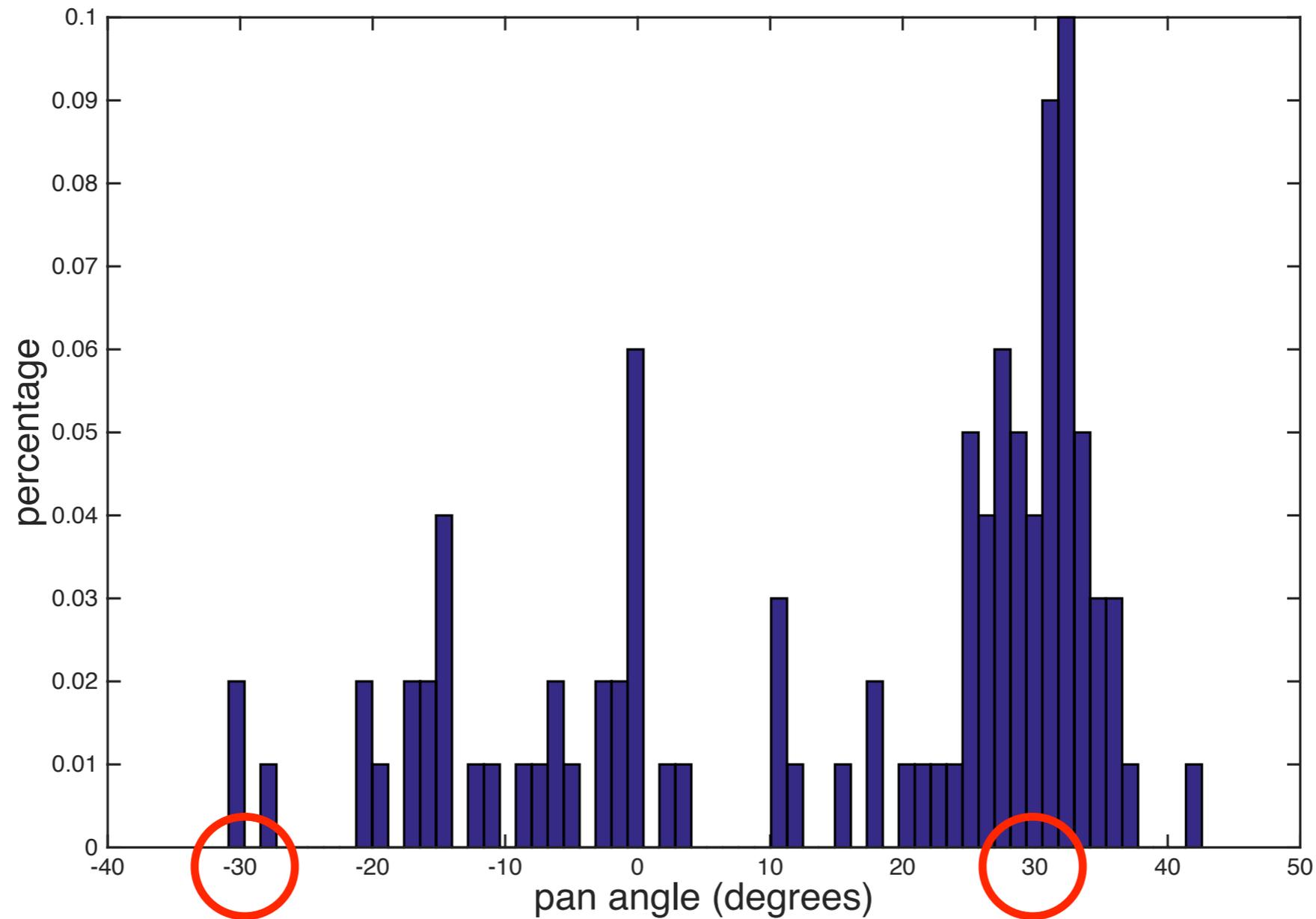


look right

Goal: analyze cameraman's view



Not always the same angle



-30°, 30° are almost opposite.

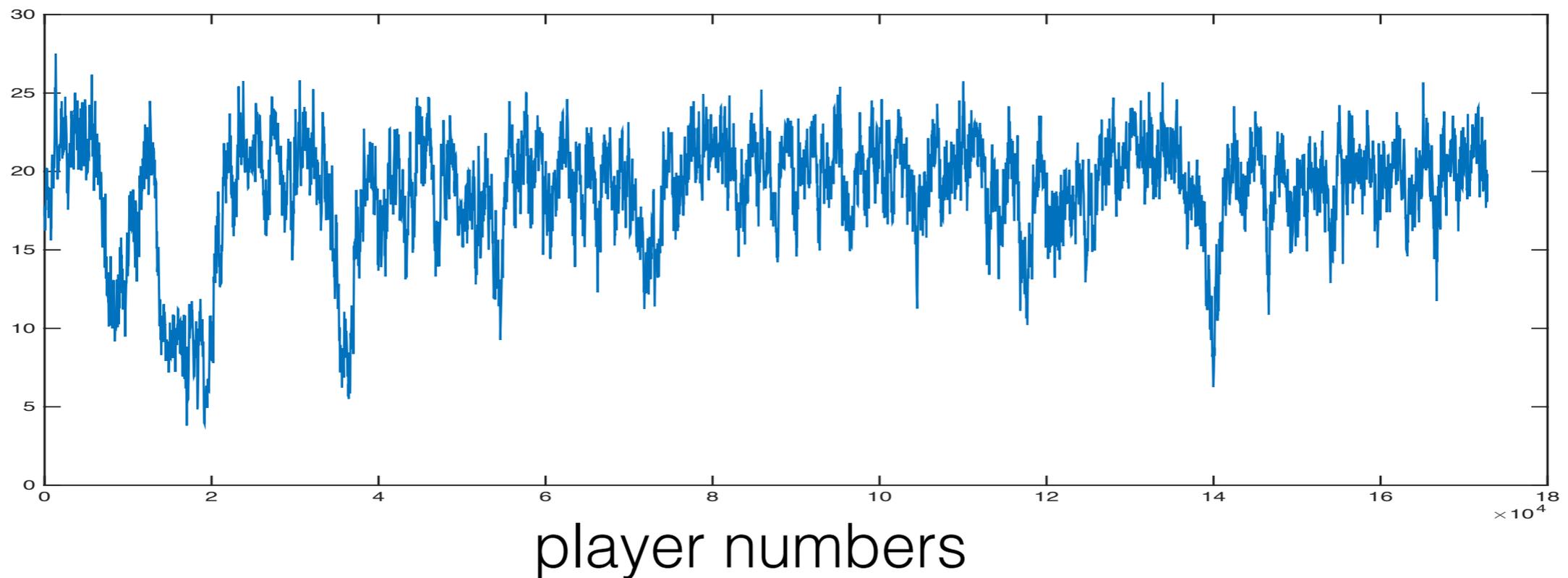
Data

48-min (172, 800 frames) soccer game

Player positions on the playing ground

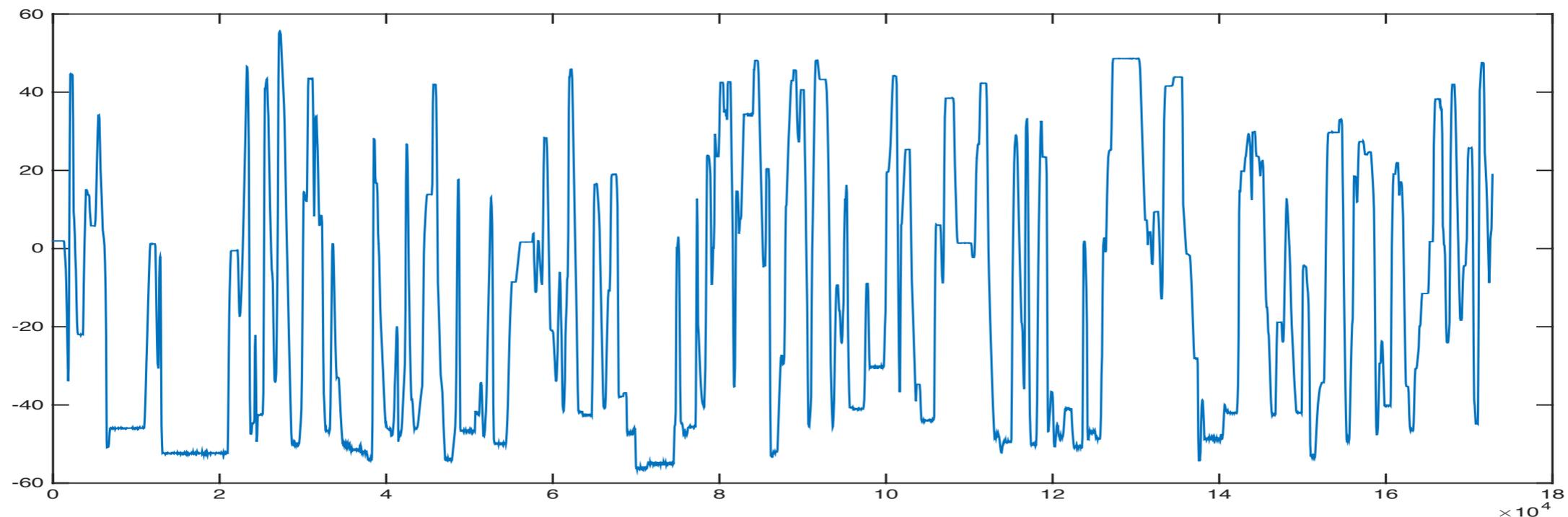
Camera angles of a PTZ camera

Both of them are noisy



Tasks

- Overview: camera angle, player position in playing ground
- Query1 : given angle get player position distribution
- Query2 : given player position get angle distribution
- Outlier detection: cameraman look at un-normal angle



camera pan angle

Linking Sentences in Online Conversations



Works and plays well with others

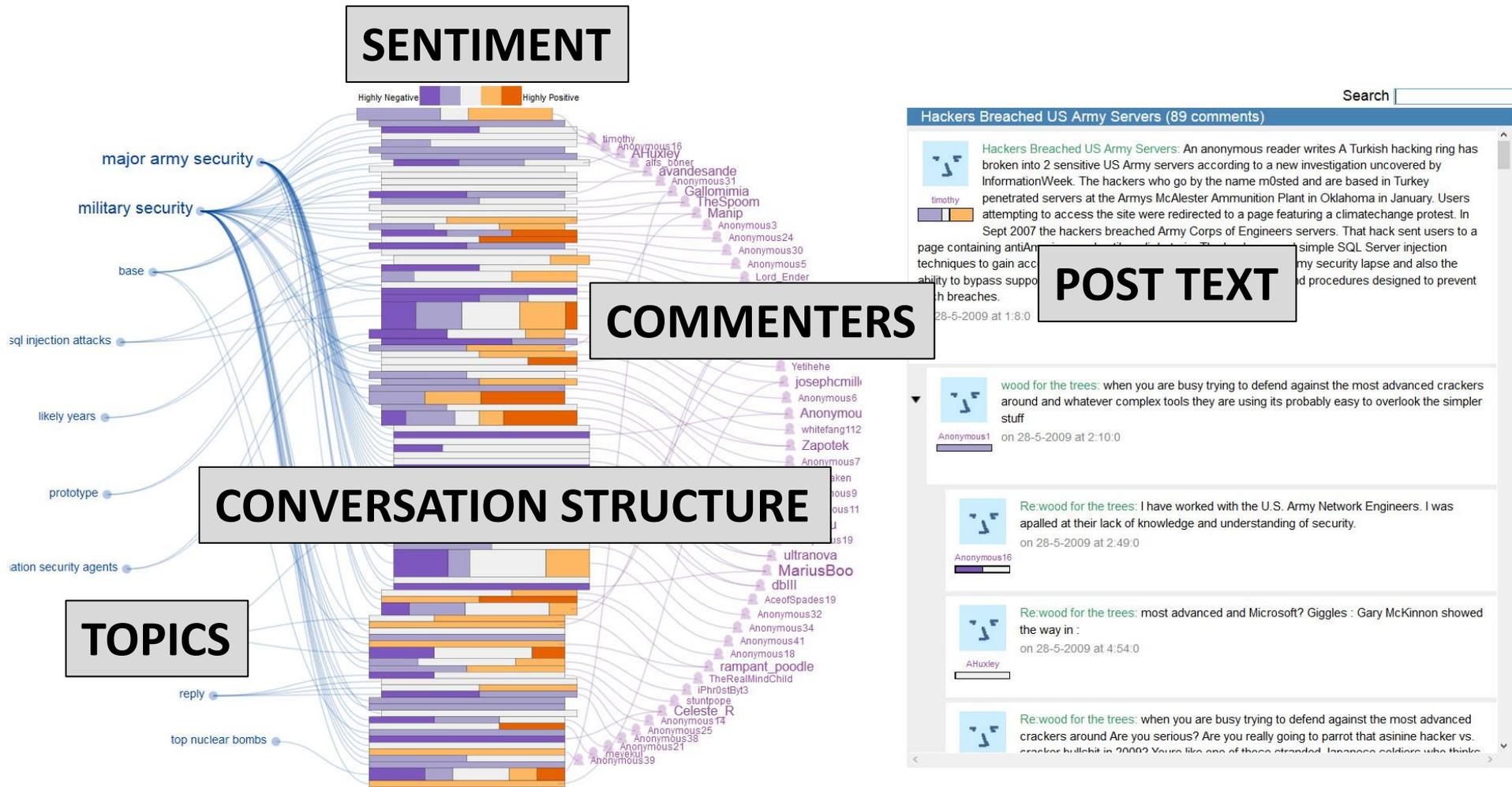
Jordon Johnson

M.Sc. Student

UBC Computer Science

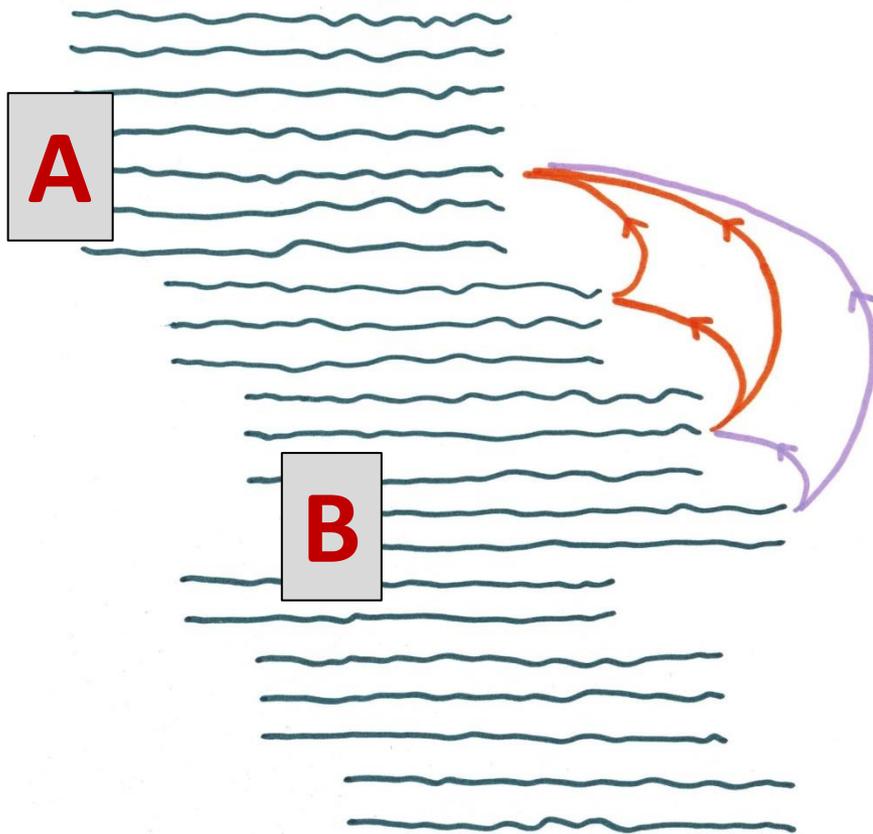
jordon@cs.ubc.ca

ConVis @ UBC



Visualizing Links Between Sentences

“Sentence **B** refers to sentence **A**”



GOAL: **visualize/edit** links

Link Attributes:

- Linked sentences
- Agreement value
- Sentiment value

Links may form chains that give additional insight into conversation structure

Data and Current Tasks

- Online conversations, annotated by humans to establish a “gold standard”
 - Not that good...
 - Use vis to **make corrections** and **improve the gold standard**
- (In progress) annotations by candidate linking algorithms
 - Use vis to **evaluate the output**

Future Tasks for NLP Researchers

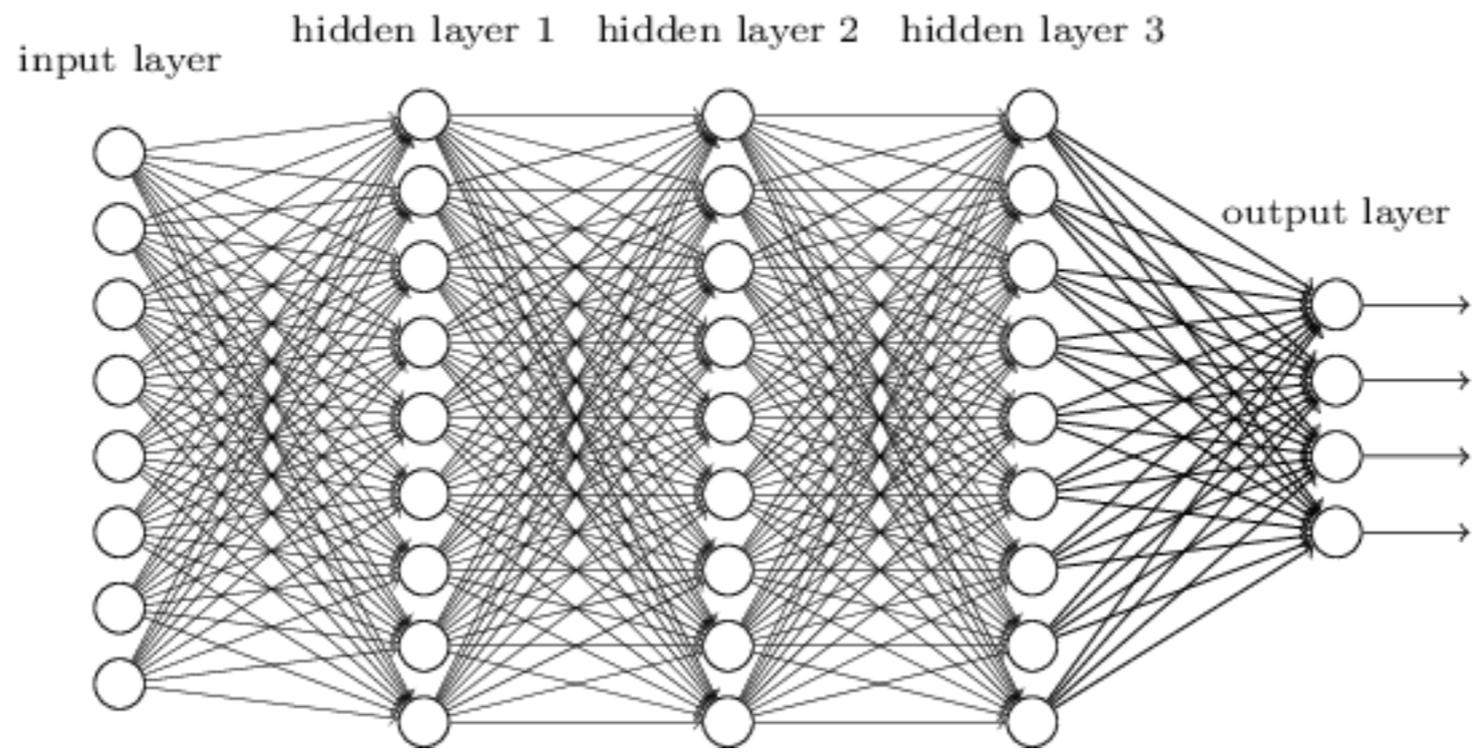
- Study link chains to associate link patterns with conversation types
 - Agreements
 - Debates
 - Off-topic/flamewars
 - Can we profile **trolling**?

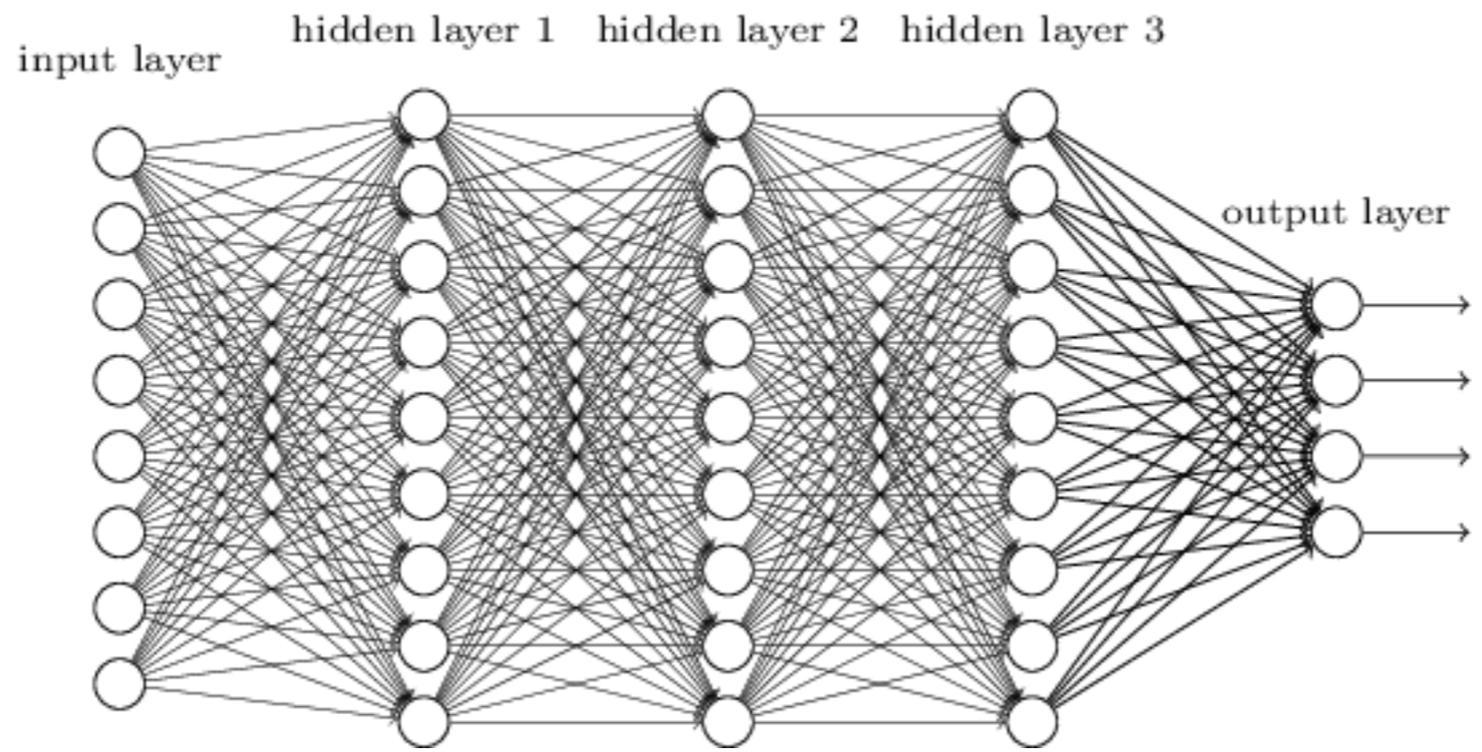


Thank you!

vidviz: scaling up video annotation

Julieta Martinez











+ “Plumeria
Frangipani”

The Internet



The Internet

--	--

The Internet



The Internet



The Internet



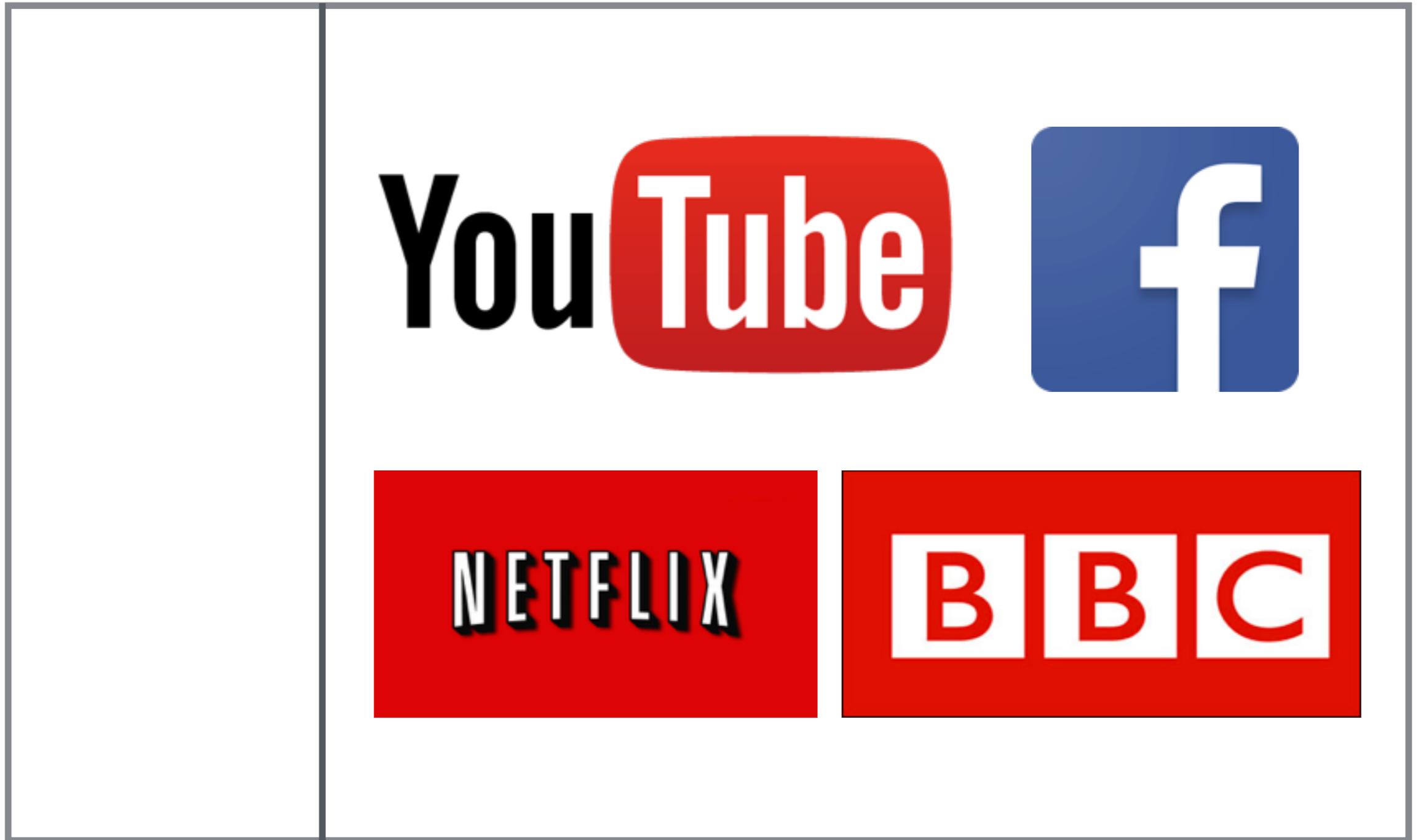
The Internet



NETFLIX

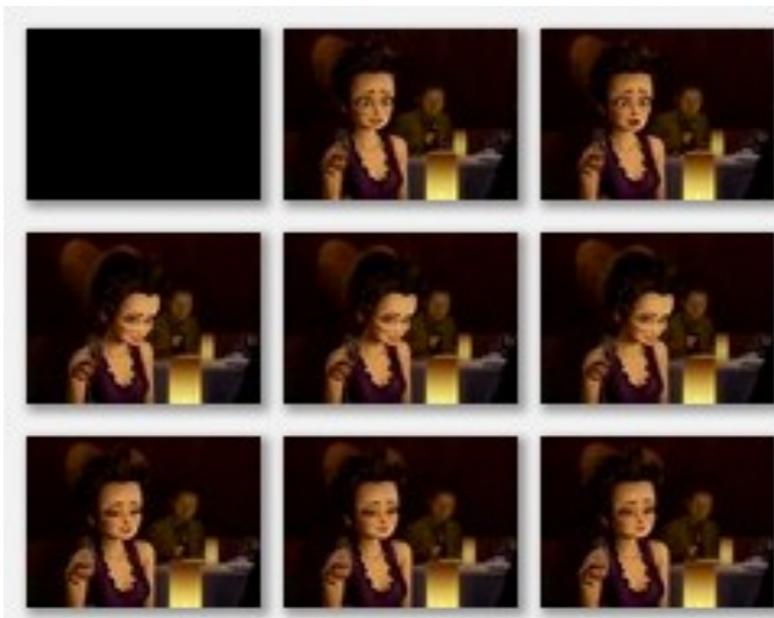
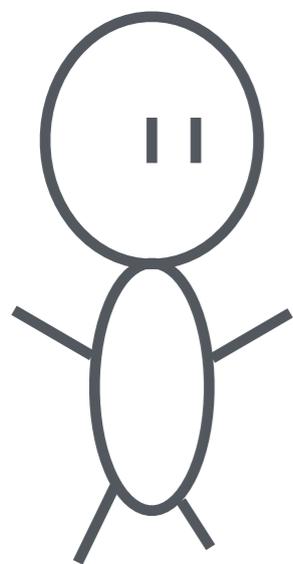
B B C

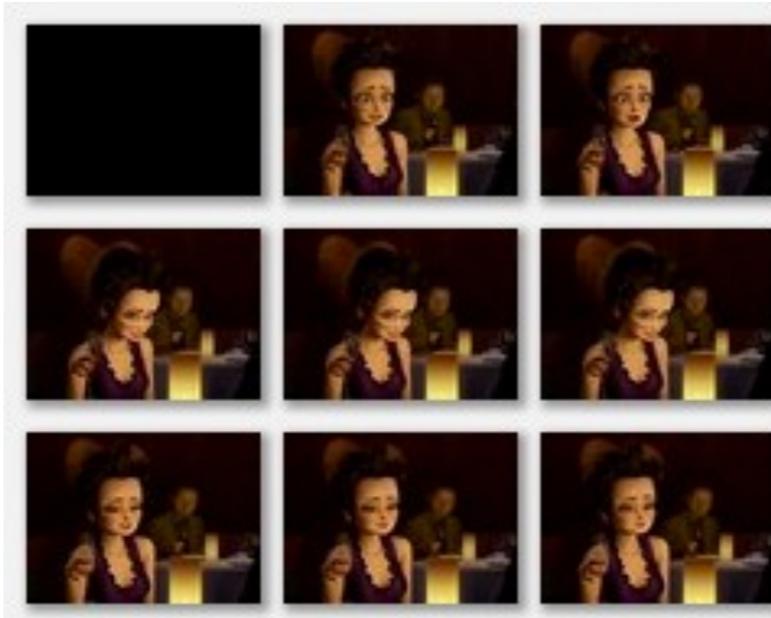
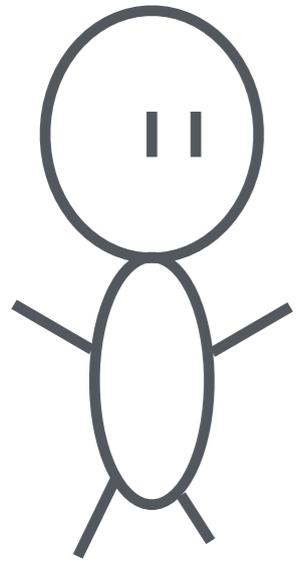
The Internet

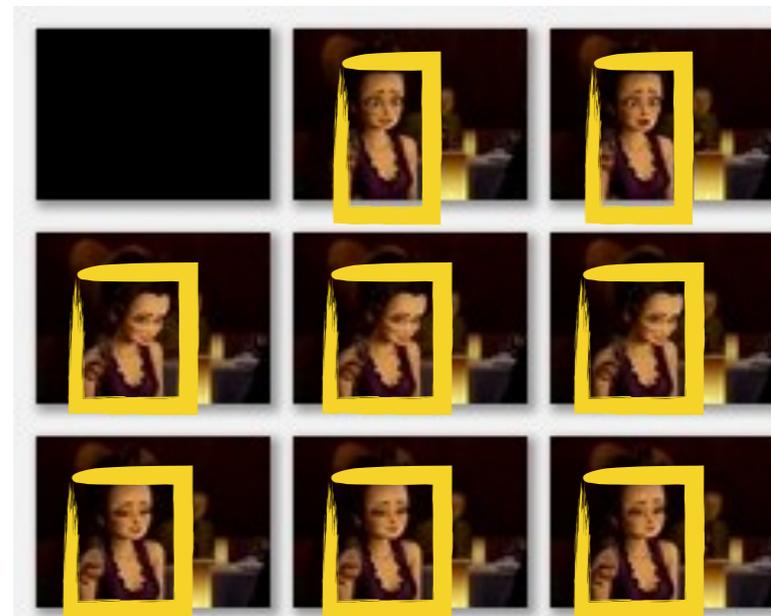
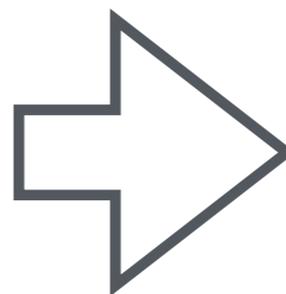
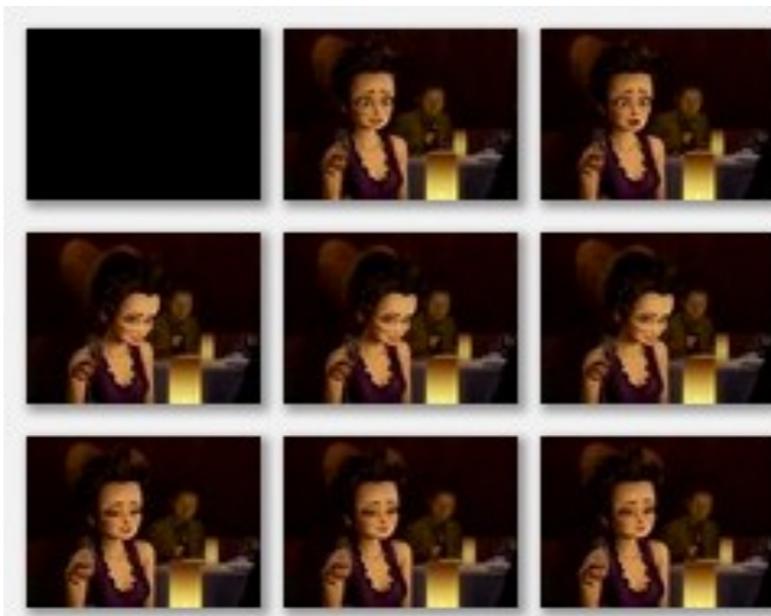
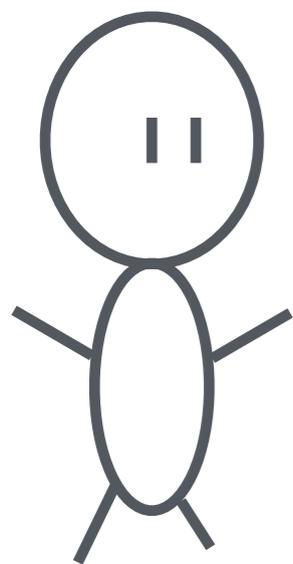


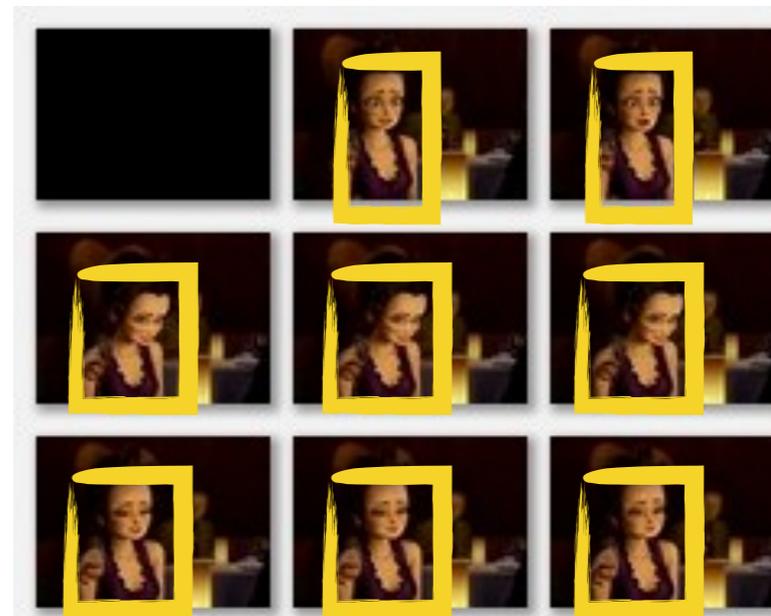
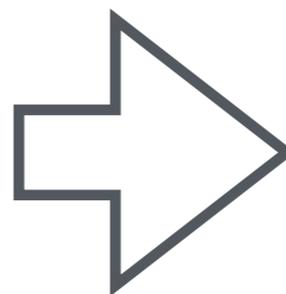
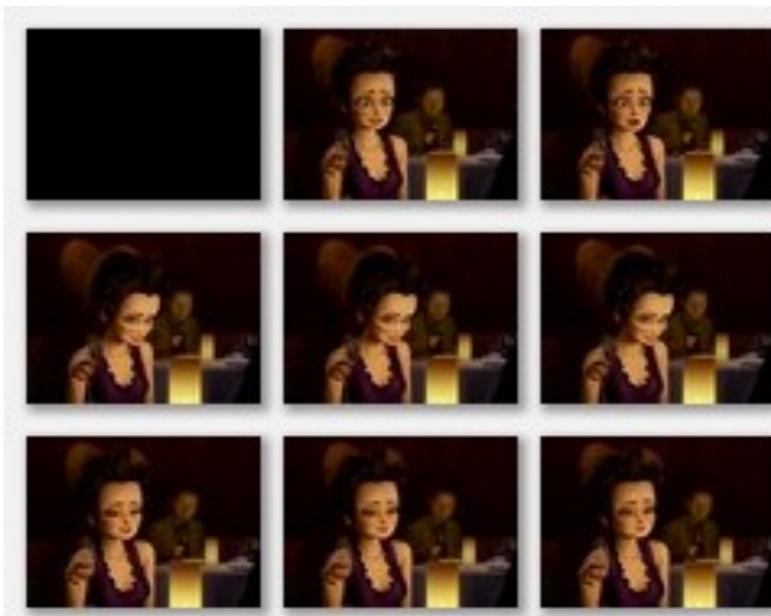
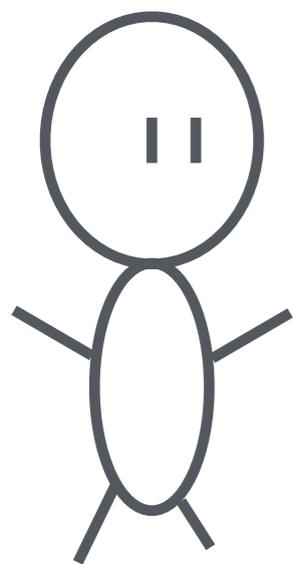
“the dark matter of the Internet” — Fei-Fei Li

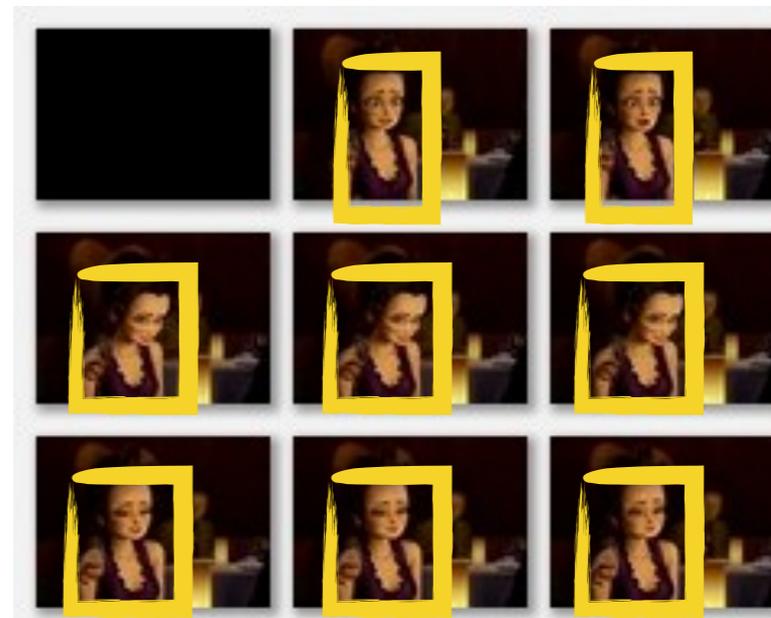
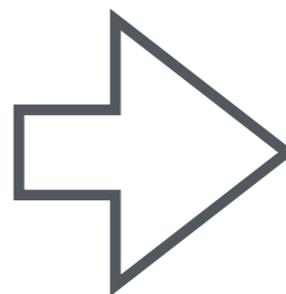
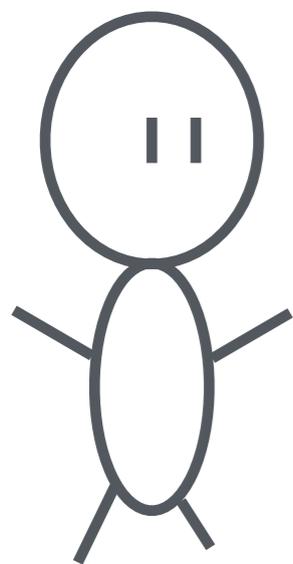


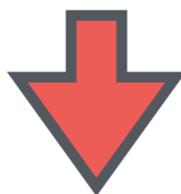
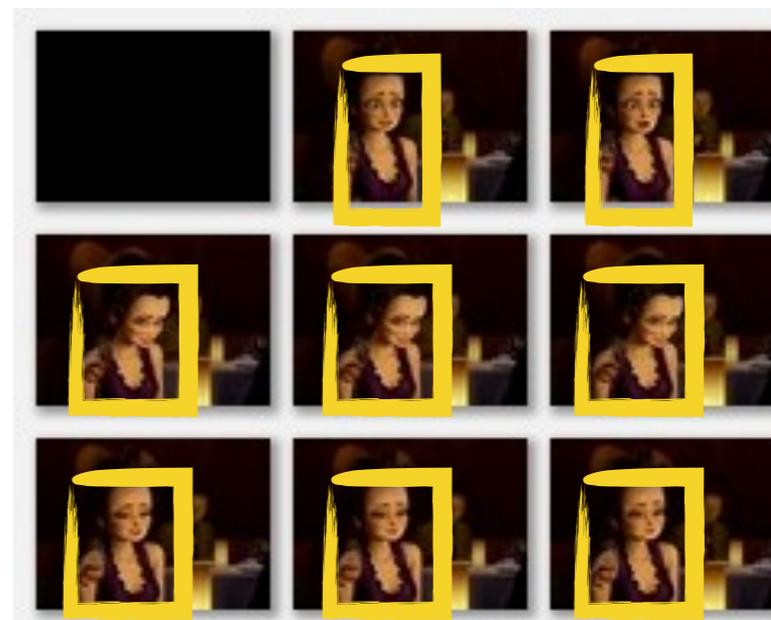
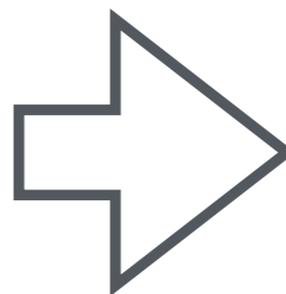
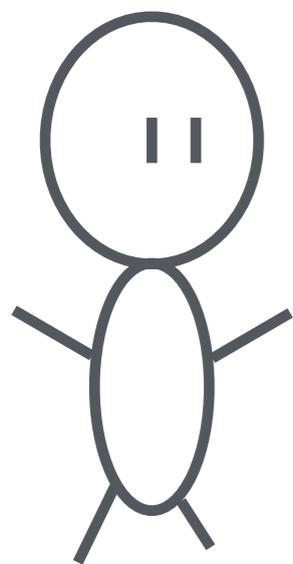


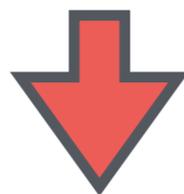
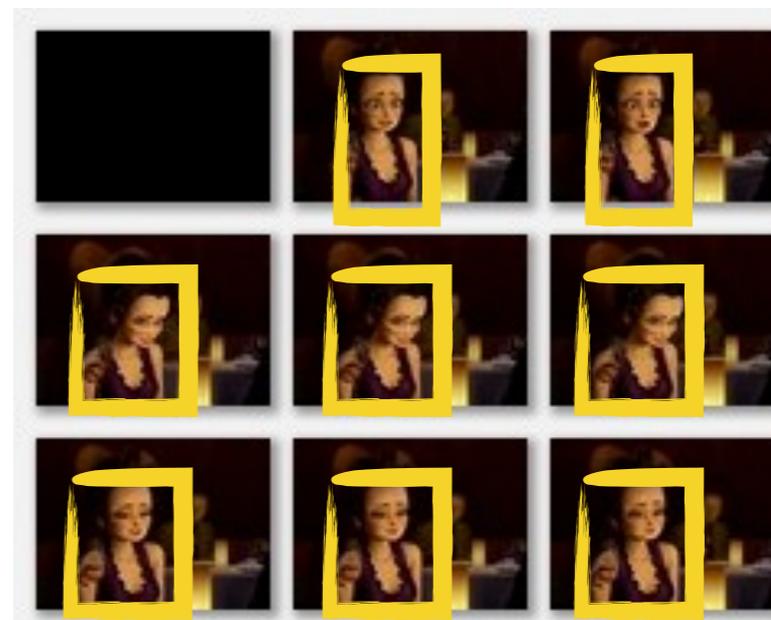
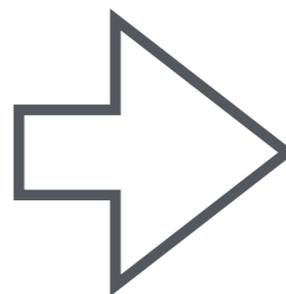
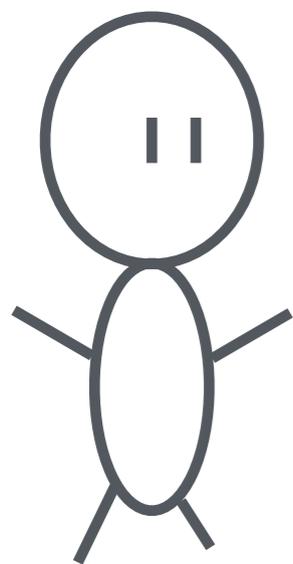


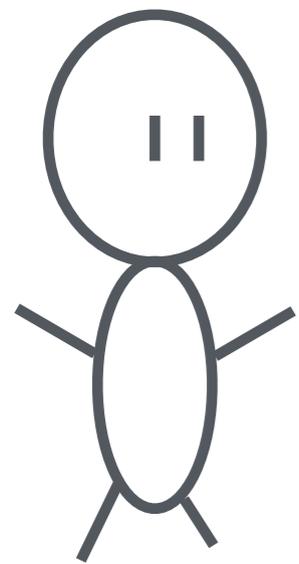




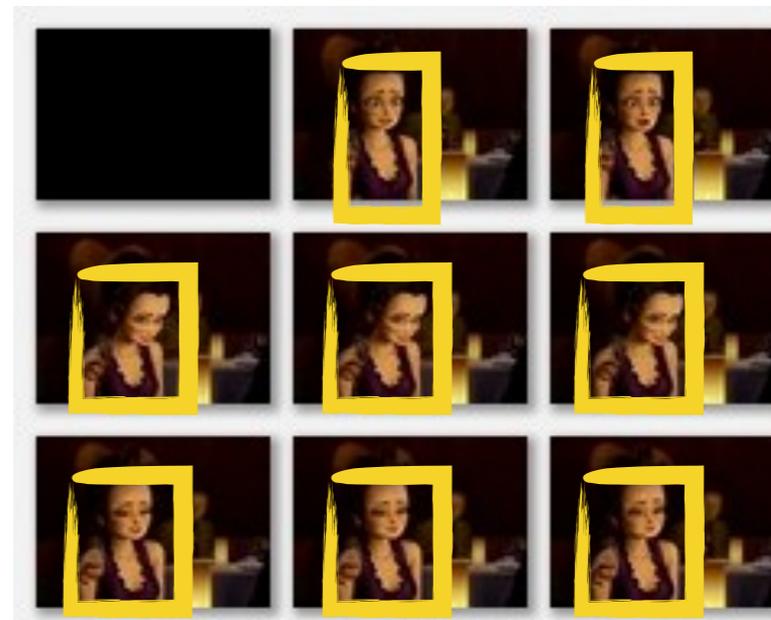
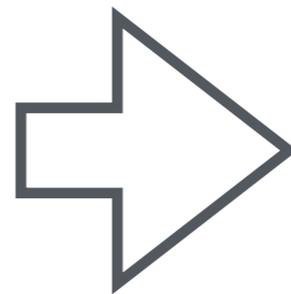




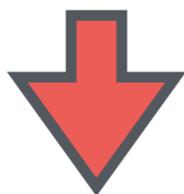




vidviz



\$



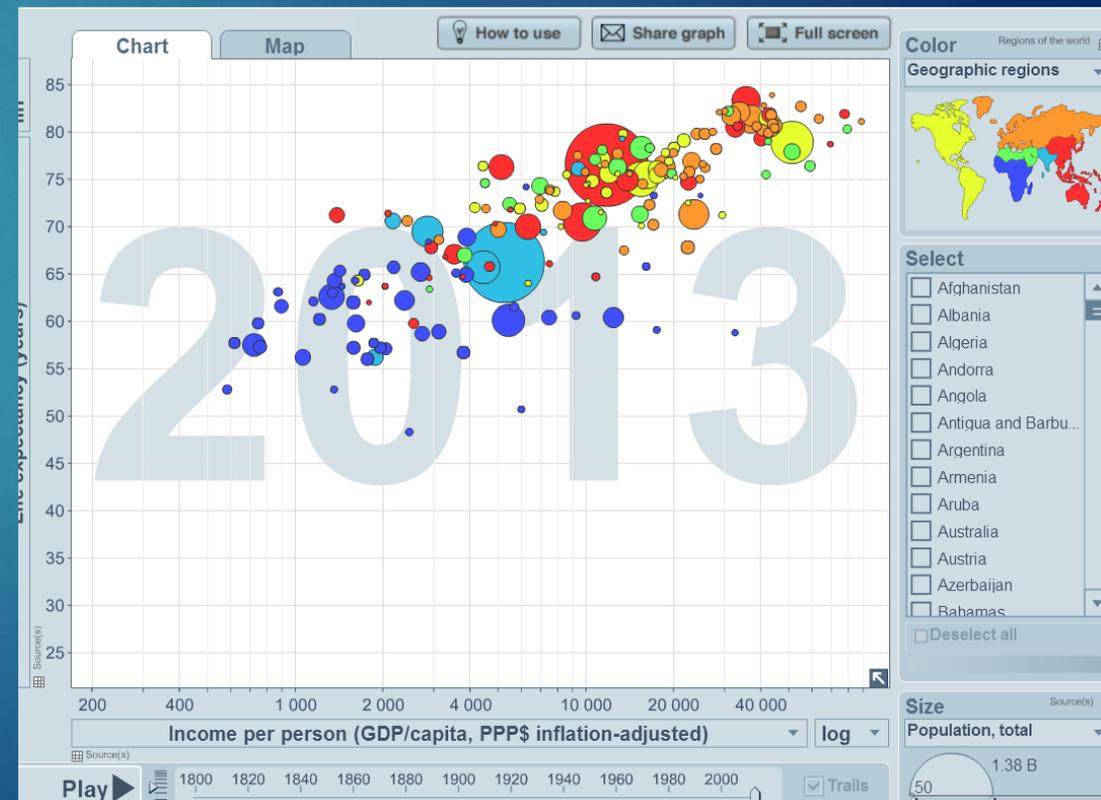
Interactive graphs using R Shiny

And maybe d3 if I have time.

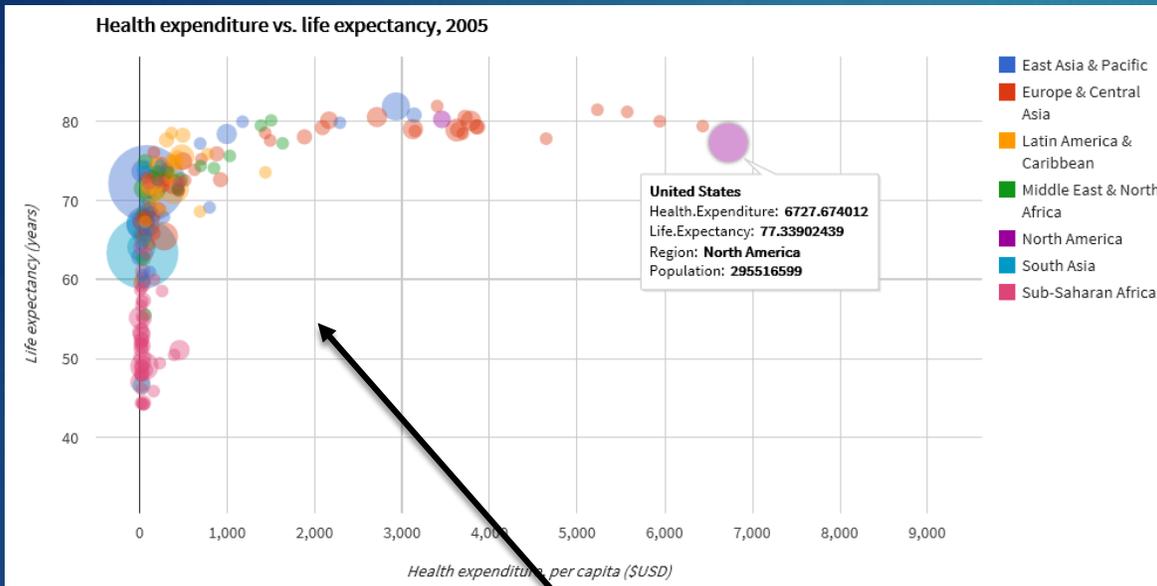
Ken Mansfield, CPSC 547, Oct 22, 2015

- ▶ Goal: Create different types of visualizations for exploration of data.
- ▶ Fully Interactive – Linked highlighting, multi-facetted, animations!
- ▶ Learn what works, what doesn't.
- ▶ Dataset: Gapminder. Wealth of information to explore, fairly easy to use.

Example: Gapminder world

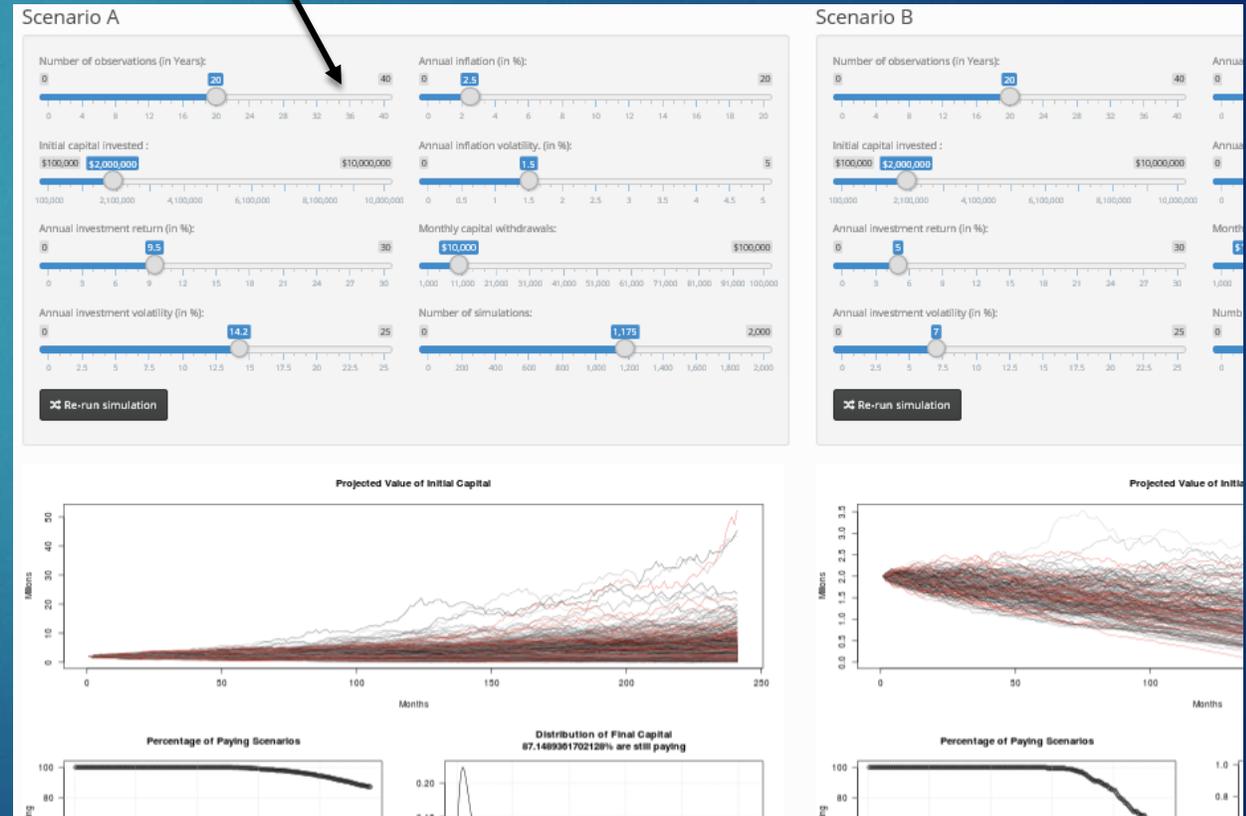


R Shiny Examples



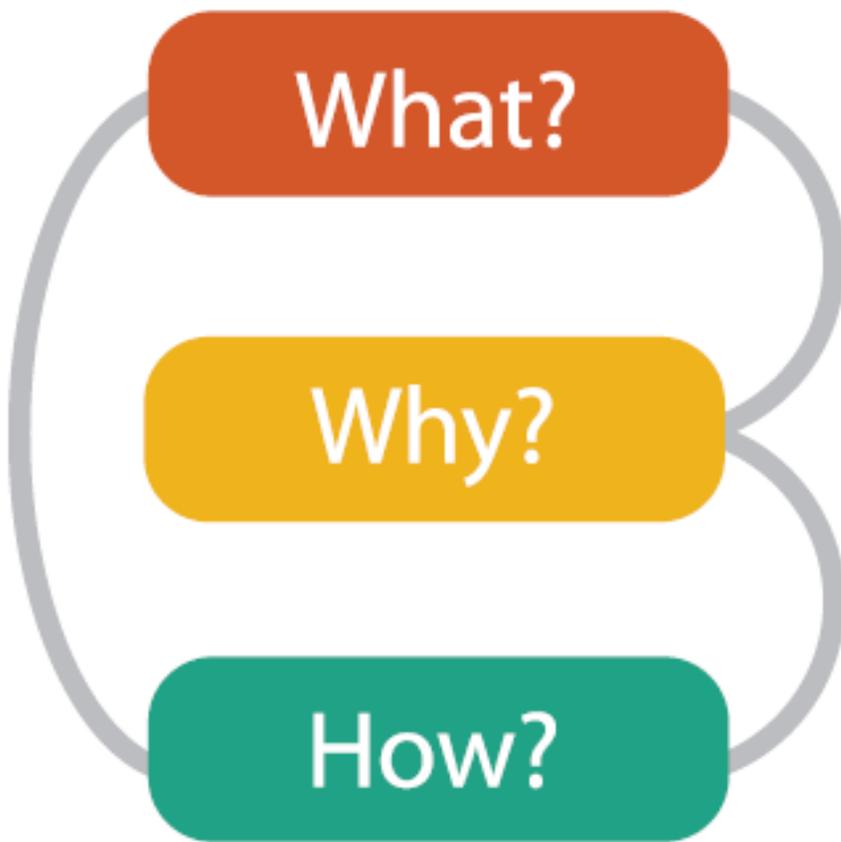
- Animation
- Colours
- Different types of Encoding

Interactivity



InfoVis Project Pitch

Kimberly Dextras-Romagnino



What?

Why?

How?

Why?

Present information to **the masses**
in a visually appealing way to both
inform and **entertain**

Storytelling: The Next Step for Visualization

- Robert Kosara

- Presentation and Communication vs Exploration and Analysis
- Data Visualization: Medium for Storytelling



WOMEN RESEARCHERS BY COUNTRY

Just one in five countries has achieved gender parity, whereby 45% to 55% of researchers are women.

SELECT COUNTRY

NORTH AMERICA
AND WESTERN
EUROPE

AVERAGE

32%

0%

75% N/A

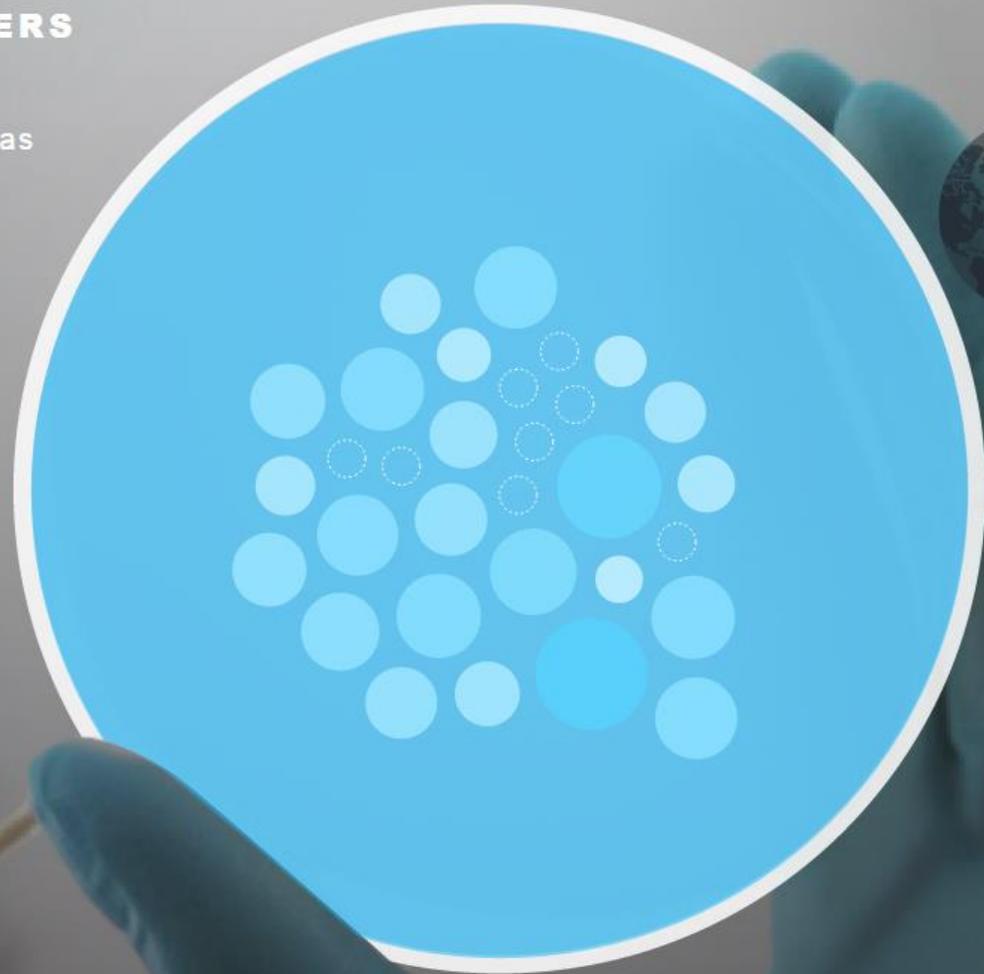


SOURCE: UNESCO INSTITUTE FOR STATISTICS



CHANGE
REGION

VIEW
MAP



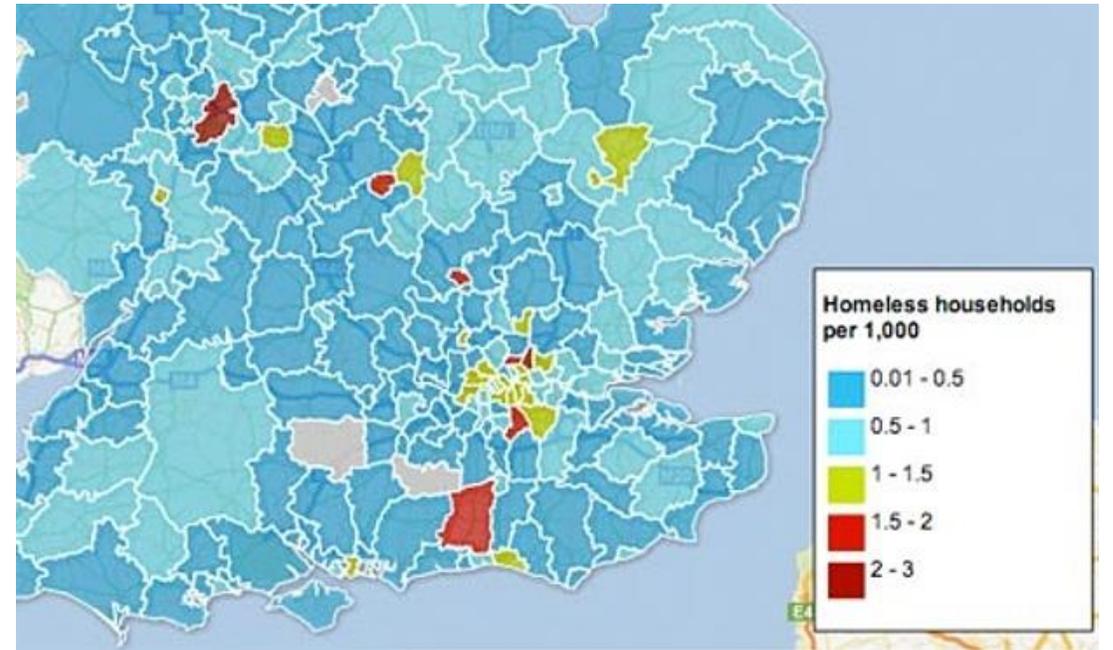
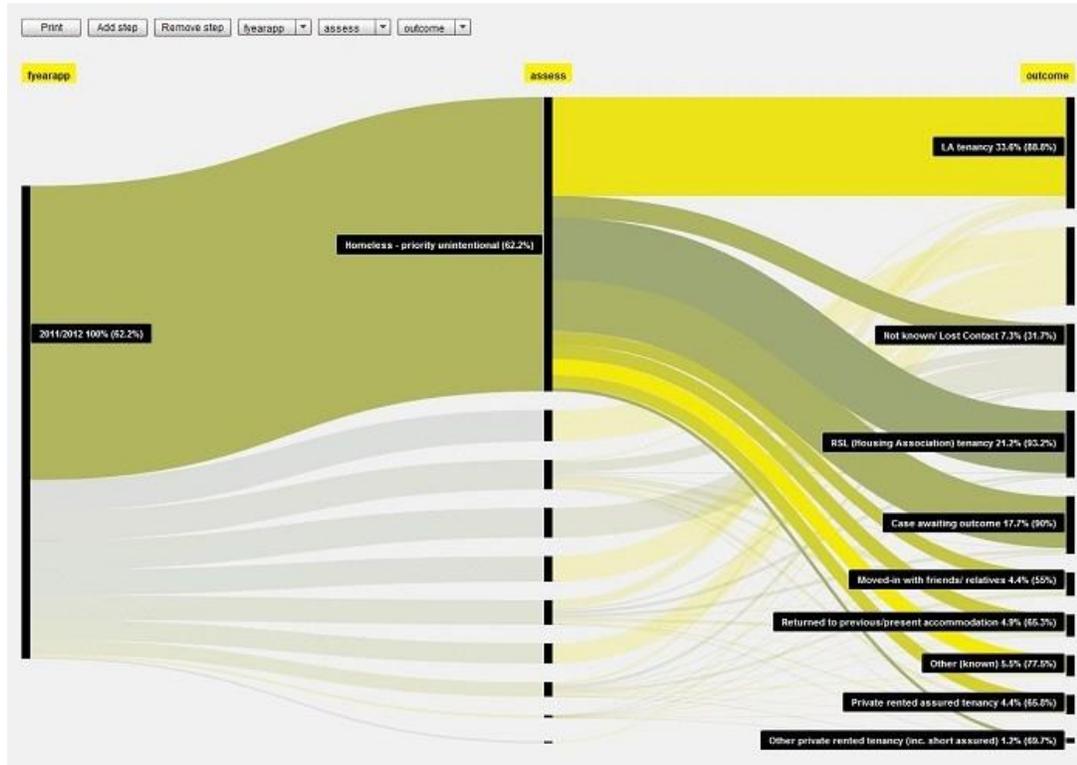
What?

Homelessness in Canada

- Things to compare
 - Areas
 - Sheltered vs Unsheltered
 - Age and Gender Distributions
 - Reasons for being on the streets



Homeless Vis Examples



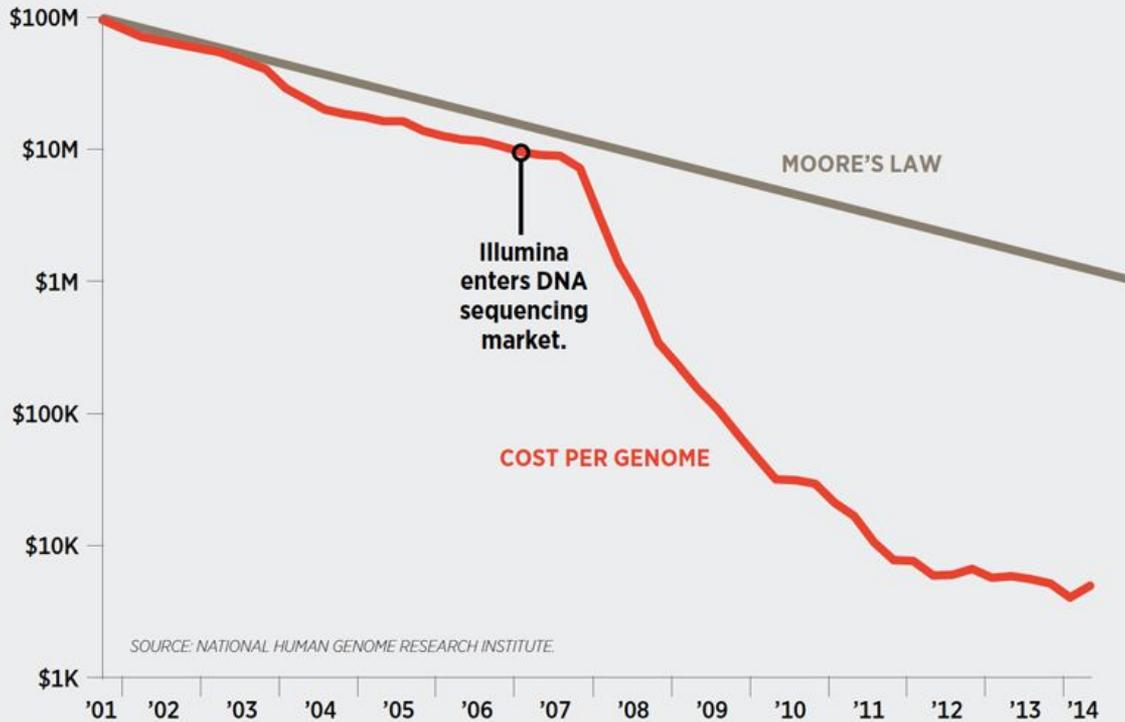
Any other ideas?

How Does Your Body Manage Its Army?

By: Louie Dinh

FLATLEY'S LAW

SINCE ILLUMINA CAME ON THE SCENE, THE COST OF SEQUENCING GENES HAS DROPPED FAR FASTER THAN PRICES PREDICTED BY MOORE'S LAW.



SOURCE: NATIONAL HUMAN GENOME RESEARCH INSTITUTE.

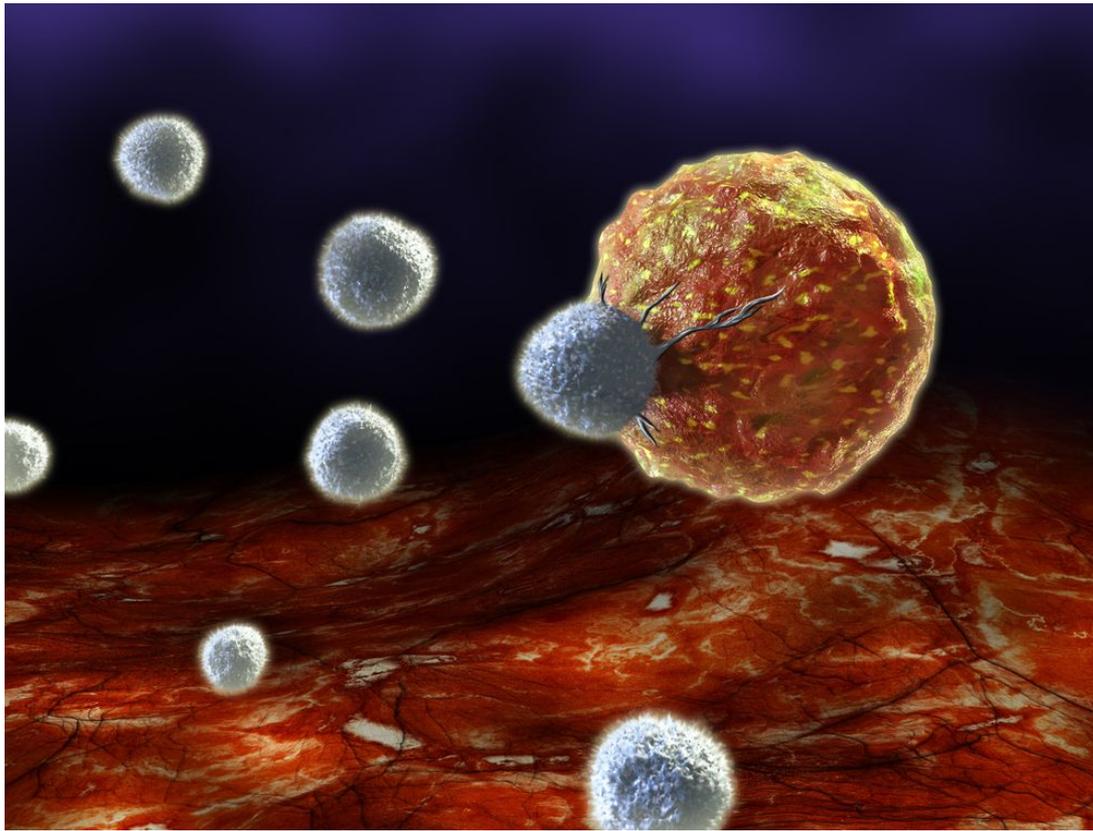
LOGARITHMIC SCALE

Anything that can be done via
sequencing will be done via sequencing

So....

Let's Quantify! (With Sequencing)

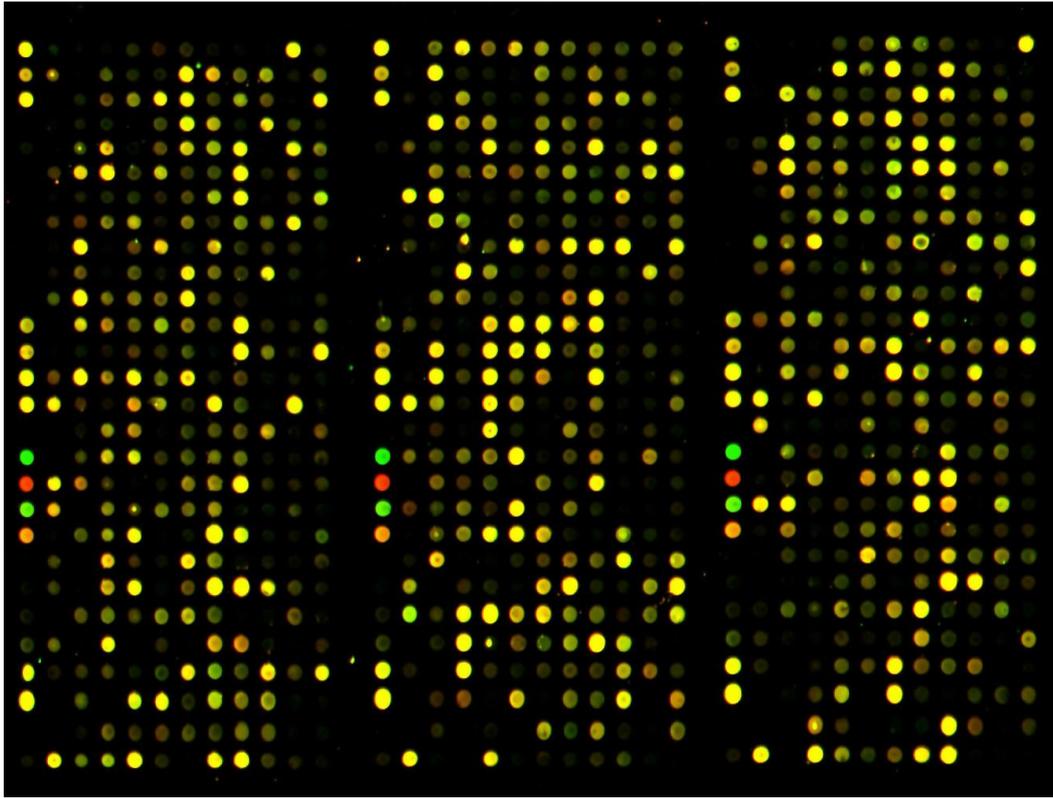
Interesting problem: How does your body manage its army (the immune system)



Which squadron (T-cells, B-Cells, Neutrophils, etc...) does it deploy and how does it coordinate this attack against invaders?

When your body starts a civil war (autoimmune disease), how does that look compared to a normal person?

Sequencing data on blood cells is
allowing us to visualize the your personal
army



Very high dimensional. Highly correlated. How do we understand it?

If you “know” biology and find this problem interesting, come talk to me!

You are just beginning your research on Cordaceae, a subject you know nothing about. Where do you begin?

- Google
- Your course syllabus
- UBC Library's Summon Search

Next

Google	50	68.5%	
Your course syllabus	5	6.8%	
UBC Library's Summon Search	18	24.7%	
<i>Total: 73</i>			

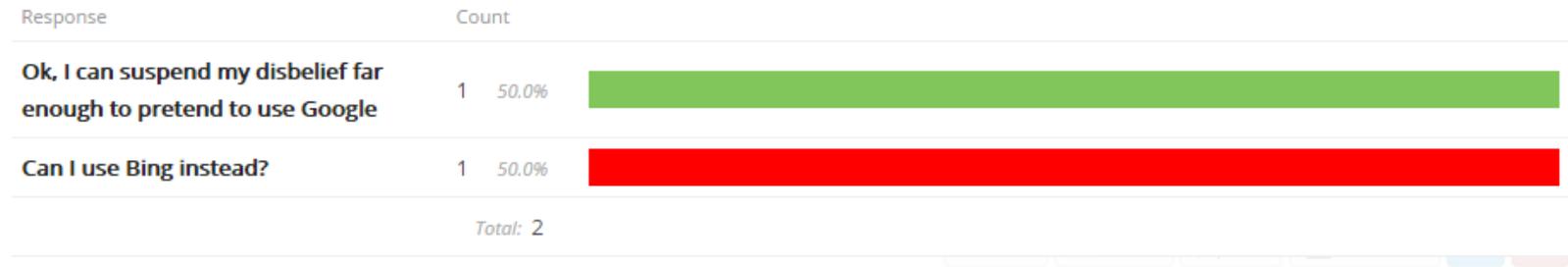
[summon]

Response	Count		
Google	12	66.7%	
Syllabus	6	33.3%	
<i>Total: 18</i>			

[syllabus1]

Response	Count		
The assignment requirements. Why else would I be researching something I know nothing about?	4	36.4%	
I think we read something about			

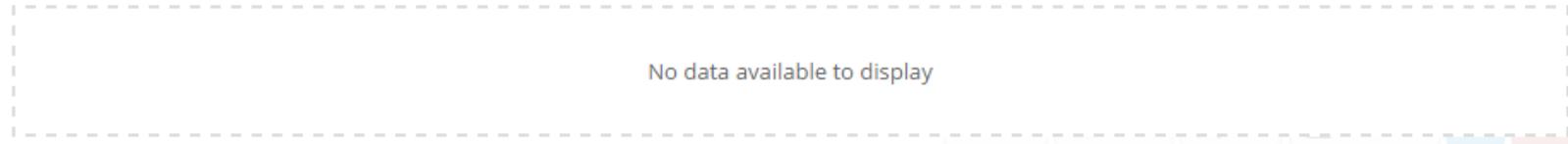
[donereadings]

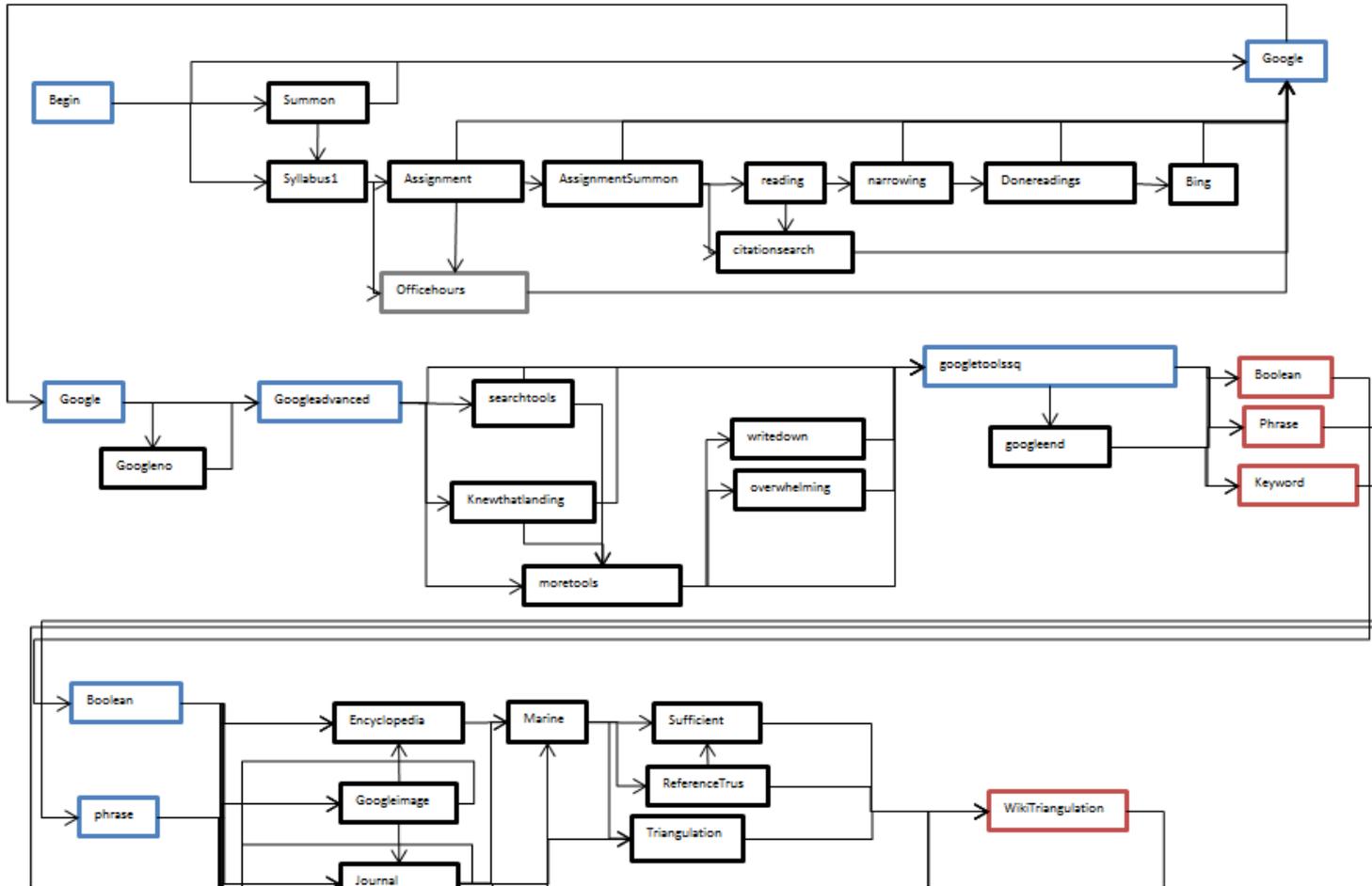


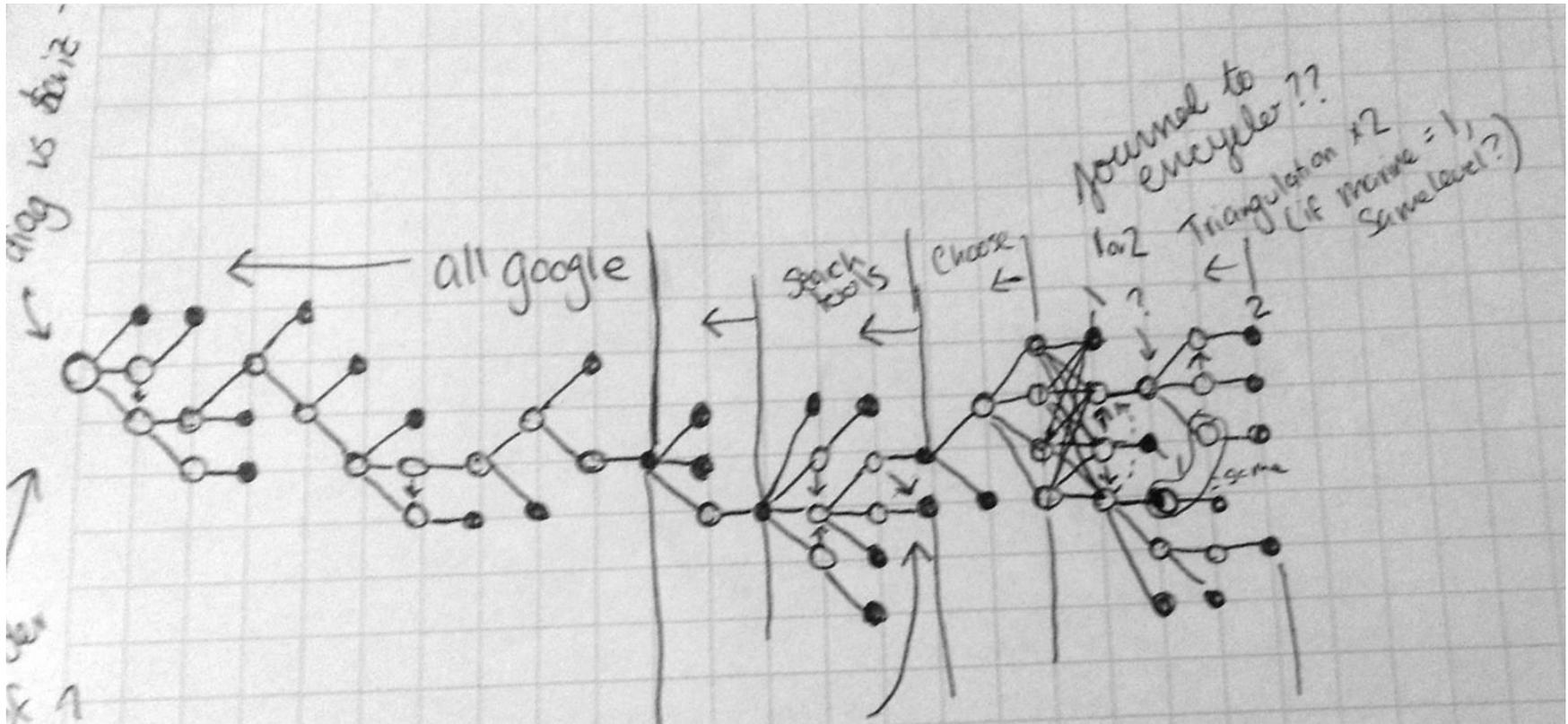
[Bing]



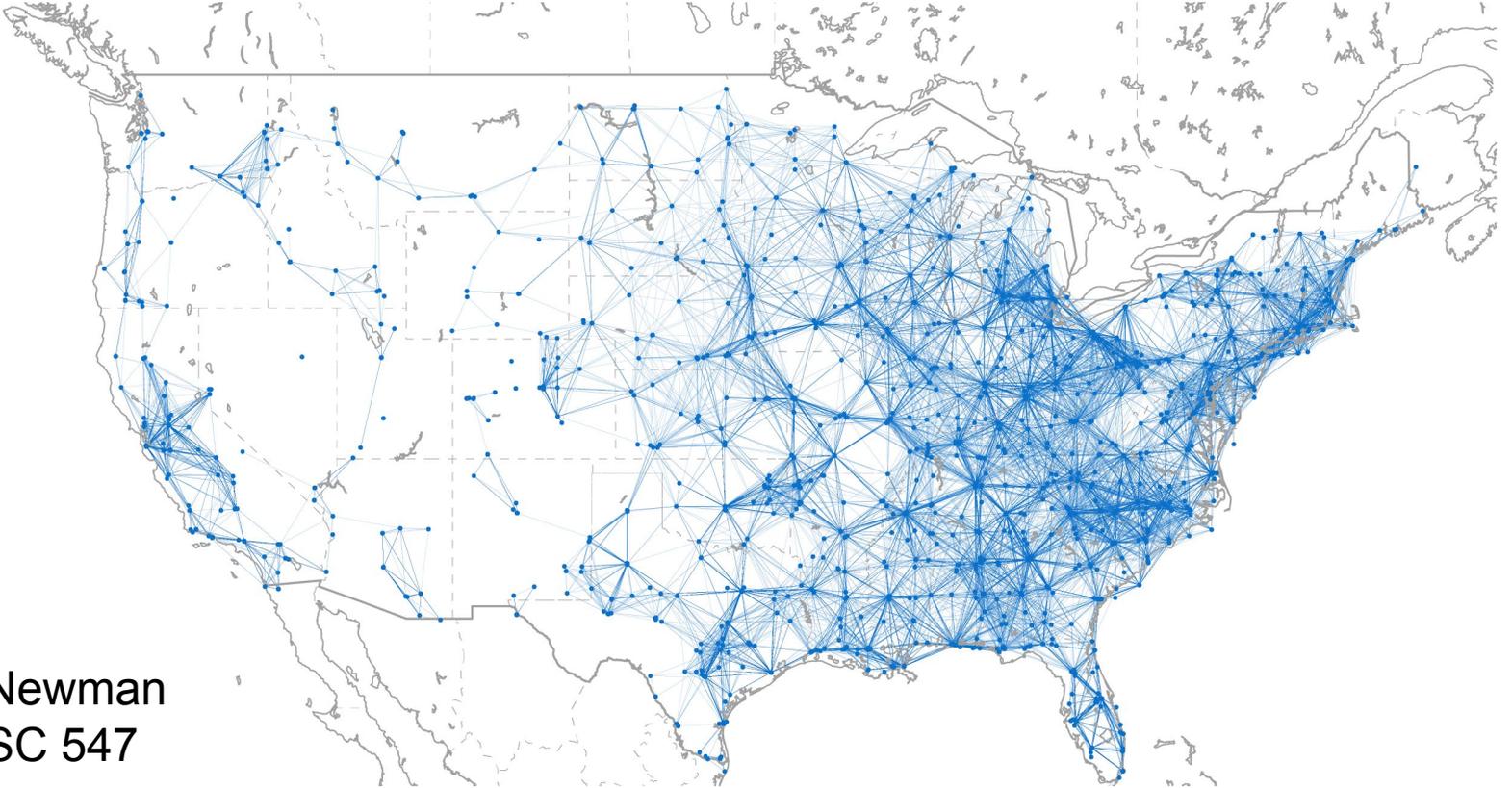
[OfficeHours]







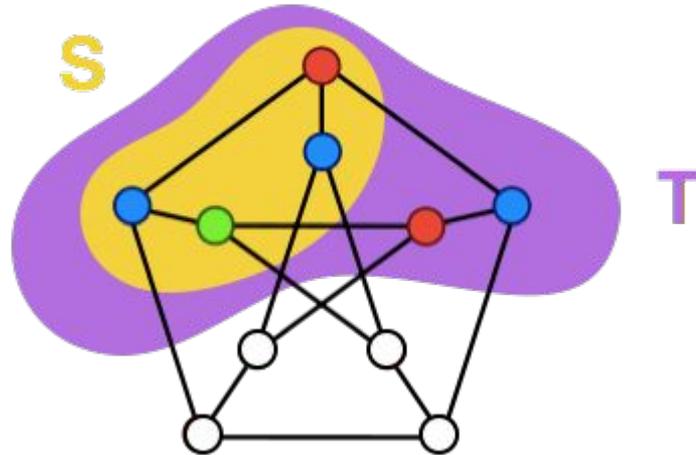
Spectrum Auction -> SAT Problems



Neil Newman
CPSC 547

Containment Caching

- Reuse solutions to already solved problems
- Larger problems are most useful



Visualizing the Cache

- Several million cache entries - need to summarize!
- How much of the multi-dimensional solution space does the cache “cover”?
- How are the stations distributed across cache entries?
- What is the key usage distribution for a given auction trace? Is this similar between traces?
- How “distant” are individual cache entries from each other?
- Potential complication: Data is not public (I’ve signed an NDA)

Search Trends Visualization



Rex Chang

Search Keywords

- Multiple Related Keywords
- Example
 - HTML5
 - → jQuery
 - → HTML5 jQuery
 - → HTML5 Canvas
 - → SVG
 - → HTML5 SVG
 - → HTML5 SVG Canvas
 - → HTML5 jQuery Canvas

What & Why

- Data: Search Engine Statistics
 - Google AdWords, Trends, Suggests
- Task: Given certain keywords, find related keywords that are:
 - Being searched more: Higher search volume
 - Getting more searched: Trending
- Rationale
 - Search Engine Optimization(SEO)
 - Search Keyword Efficiency

Example

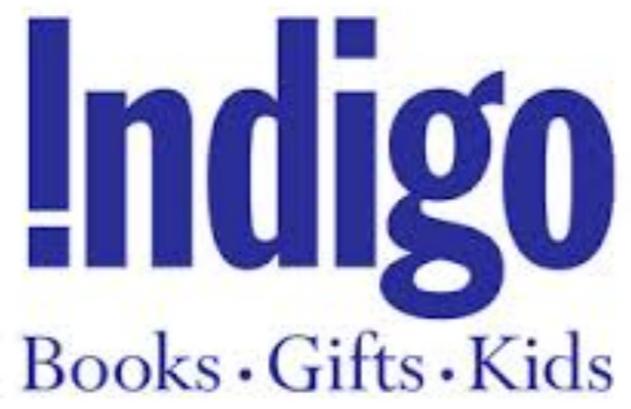
- HTML5: 368000
 - → jQuery: 823000
 - → HTML5 jQuery: 720
 - → HTML5 Canvas: 22200
 - → SVG: 11000
 - → HTML5 SVG: 2400
 - → HTML5 SVG Canvas: 140
 - → HTML5 jQuery Canvas: 90

Example

	(null)	HTML5	HTML5 canvas
(null)		368000	22200
jQuery	823000	720	90
SVG	110000	2400	140

Visualizing a SAP Network





SEARCH

PROG-ZP6_NTSKK_LIST_ACTIVITY_V2

SET ORDER **USERS**

GLOBAL SORT BY **CONNECTIONS**

USAGE 13 71

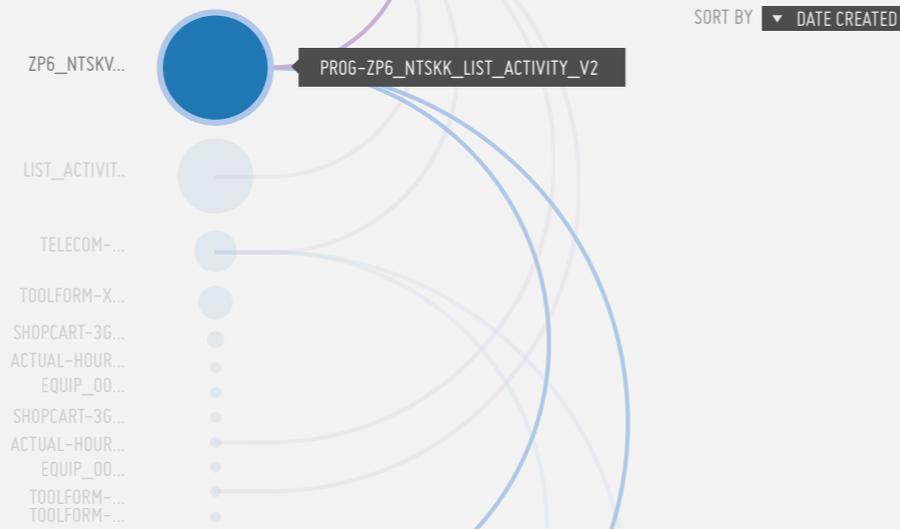
PERFORMANCE 8 20

DEGREE 0 10

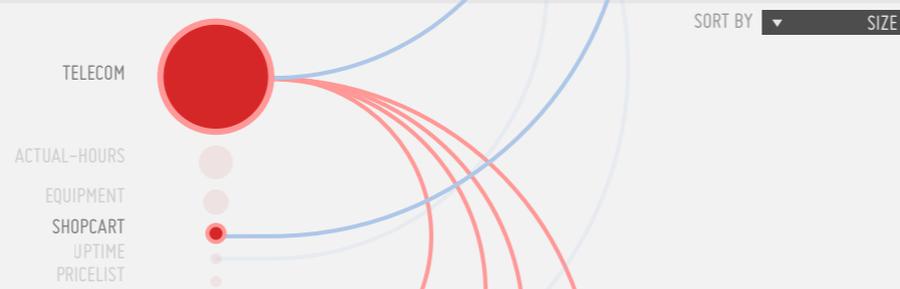
USERS



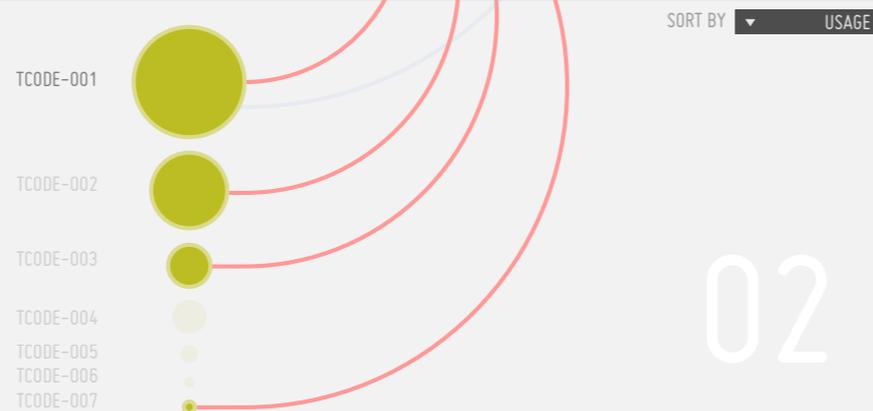
PROGRAMS



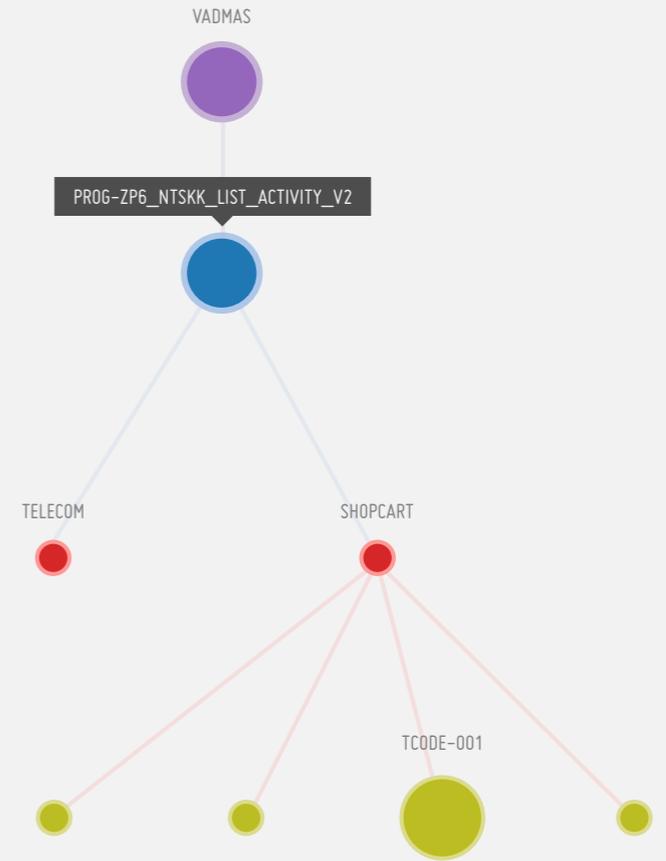
TABLES



TCODES



SCALE BY PERFORMANCE



03

PROG-ZP6_NTSKK_LIST_ACTIVITY_V2

EXPORT CSV



04

01

02



© BCTV Malaysia

547 Information
Visualization
Pitches - Thu. Oct 22, 2015



Yaashaar Hadadian
Fast Track Ph.D. Student in CS Dept
cs.ubc.ca/~hadadian



© BCTV Malaysia

Motivation

Used to be a TV presenter
Had many talk shows
Wrote/Directed ~200 episodes

\$0,

Viewers' ratings mattered (\$\$)

- Keeping up w/ trends
- Touching popular genres
- & 100s of more analyses

Movie Databases

Our heaven!

A university to learn:

- what work(ed)/(s)
- what didn't/doesn't

Guess
what?

I'm planning
to visualize
the heaven!



Data set

From movielens.org
Ratings until Aug 2015 !

2 versions are available:

Light

- 700 Users
- 9K Movies
- 100K Ratings

Full

- 230K Users
- 30K Movies
- 21M Ratings



Data set

Features

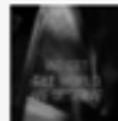
- + Titles
- + Genre
- + Rating
- + Tags (Themes)
- IMDB ID!
 - + IMDB Rating
 - + Metascore
 - + Year
 - + Director
 - + Writer
 - + Awards
 - ++ Many more...

Highest Rated TV Series With At Least 5,000 Votes

1-50 of 996 titles.

Next »

Sort by: Popularity | A-Z | **User Rating** ▼ | Num Votes | US Box Office | Runtime | Year | US Release Date

1.		Breaking Bad (2008 TV Series) ★★★★★ 9.5/10 A chemistry teacher diagnosed with terminal lung cancer teams up with his former student to cook and sell crystal meth. With: Bryan Cranston, Aaron Paul, Anna Gunn Crime Drama Thriller 47 mins. TV-14	Add to Watchlist
2.		Game of Thrones (2011 TV Series) ★★★★★ 9.5/10 Several noble families fight for control of the mythical land of Westeros. With: Emilia Clarke, Peter Dinklage, Kit Harington Adventure Drama Fantasy 56 mins. TV-MA	Add to Watchlist
3.		The Wire (2002 TV Series) ★★★★★ 9.3/10 Baltimore drug scene, seen through the eyes of drug dealers and law enforcement. With: Dominic West, Lance Reddick, Sonja Sohn Crime Drama Thriller 59 mins. TV-MA	Add to Watchlist
4.		Rick and Morty (2013 TV Series) ★★★★★ 9.3/10 An animated series that follows the exploits of a super scientist and his not so bright grandson. With: Justin Rolland, Chris Parnell, Spencer Grammer Animation Adventure Comedy Sci-Fi 22 mins. TV-14	Add to Watchlist
5.		Sherlock (2010 TV Series) ★★★★★ 9.3/10 A modern update finds the famous sleuth and his doctor partner solving crime in 21st century London. With: Benedict Cumberbatch, Martin Freeman, Una Stubbs Crime Drama Mystery 88 mins. TV-14	Add to Watchlist
6.		The Sopranos (1999 TV Series) ★★★★★ 9.2/10 New Jersey mob boss, Tony Soprano, deals with personal and professional issues in his home and business life. With: James Gandolfini, Lorraine Bracco, Edie Falco Crime Drama 55 mins. TV-MA	Add to Watchlist
7.		Last Week Tonight with John Oliver (2014 TV Series) ★★★★★ 9.2/10 Former Daily Show Correspondent John Oliver brings his persona to this new weekly news satire program. With: John Oliver, David Kaye, Noel MacNeal Comedy News Talk-Show 30 mins. TV-MA	Add to Watchlist
8.		True Detective (2014 TV Series) ★★★★★ 9.2/10 An anthology series in which police investigations unearth the personal and professional secrets	Add to Watchlist



Challenges

The DS needs some work

- Variable Recoding
- Data Cleaning
- Remote Data Fetching

It's a programming project

- HTML/CSS/JavaScript
- JQuery/D3.js
- Java/JSP/JSF



© BCTV Malaysia

I'm looking for a partner,
Wanna join me?

Visualizing Uncertainty in Incomplete Election Data

CPSC 547 Project Pitch

Yasha Pushak

Federal election results

Leading and elected

Liberal majority

Majority

338

LIB

Elected: 184
Lead: 0

184

39.5%

CON

Elected: 99
Lead: 0

99

31.9%

NDP

Elected: 44
Lead: 0

44

19.7%

BQ

Elected: 10
Lead: 0

10

4.7%

GRN

Elected: 1
Lead: 0

1

3.5%

IND

Elected: 0
Lead: 0

0

0.2%

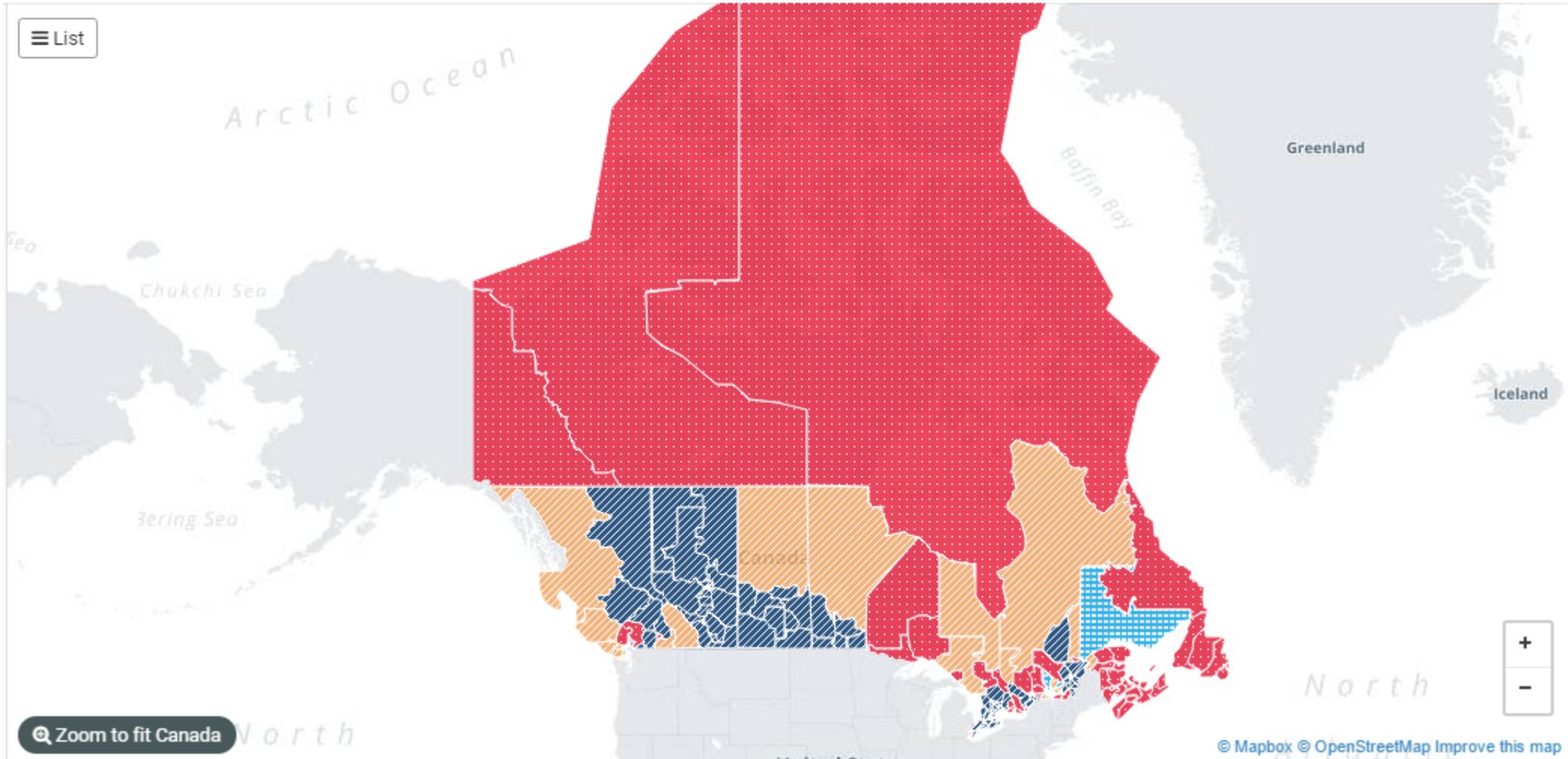
OTH

Elected: 0
Lead: 0

0

0.6%

List



Zoom to fit Canada

© Mapbox © OpenStreetMap Improve this map

Federal election results

Leading and elected

Liberal majority

Majority

338

LIB

Elected: 184
Lead: 0

184

39.5%

CON

Elected: 99
Lead: 0

99

31.9%

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Elected: 44
Lead: 0

44

19.7%

BQ

Elected: 10
Lead: 0

10

4.7%

GRN

Elected: 1
Lead: 0

1

3.5%

IND

Elected: 0
Lead: 0

0

0.2%

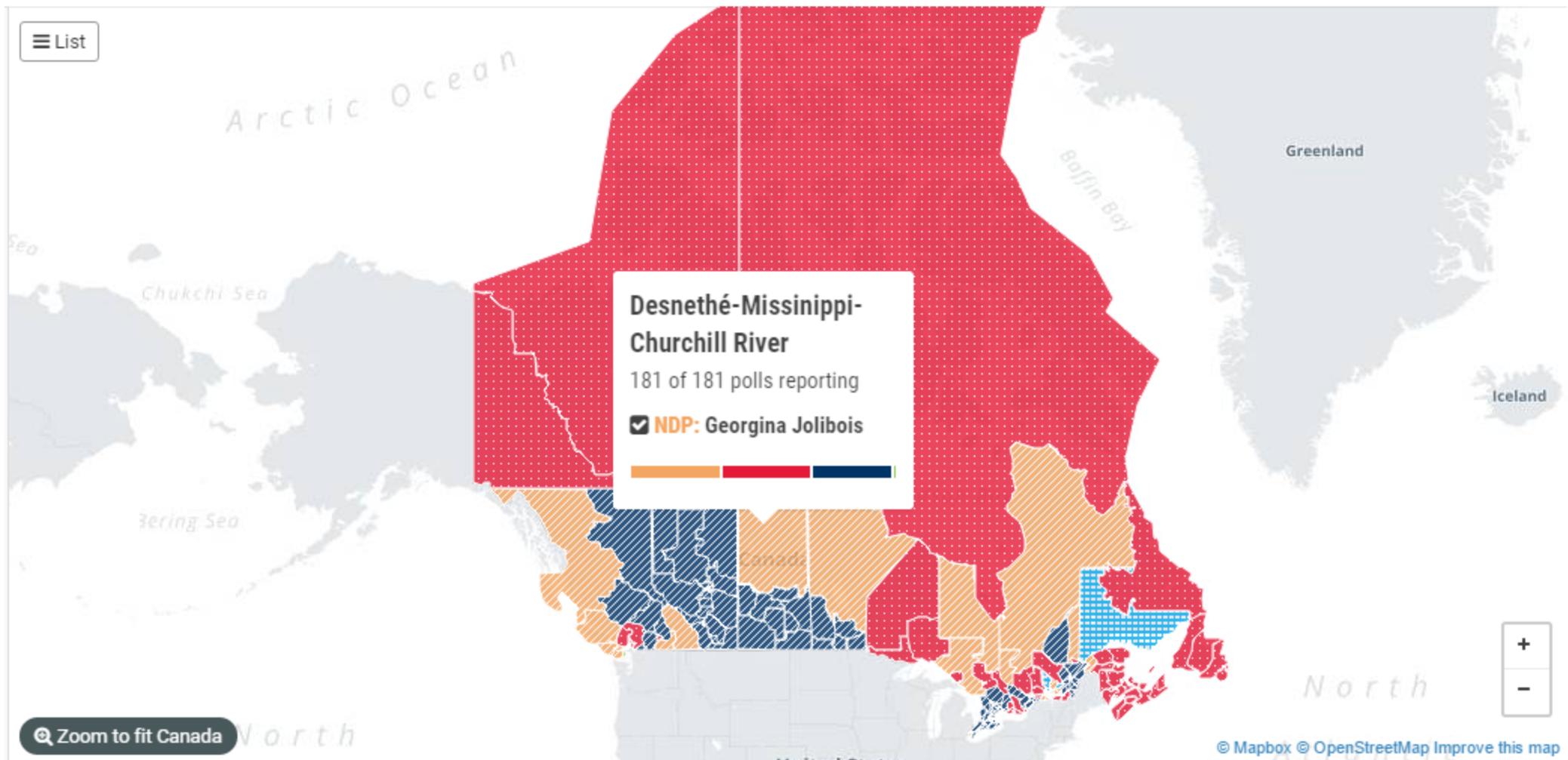
OTH

Elected: 0
Lead: 0

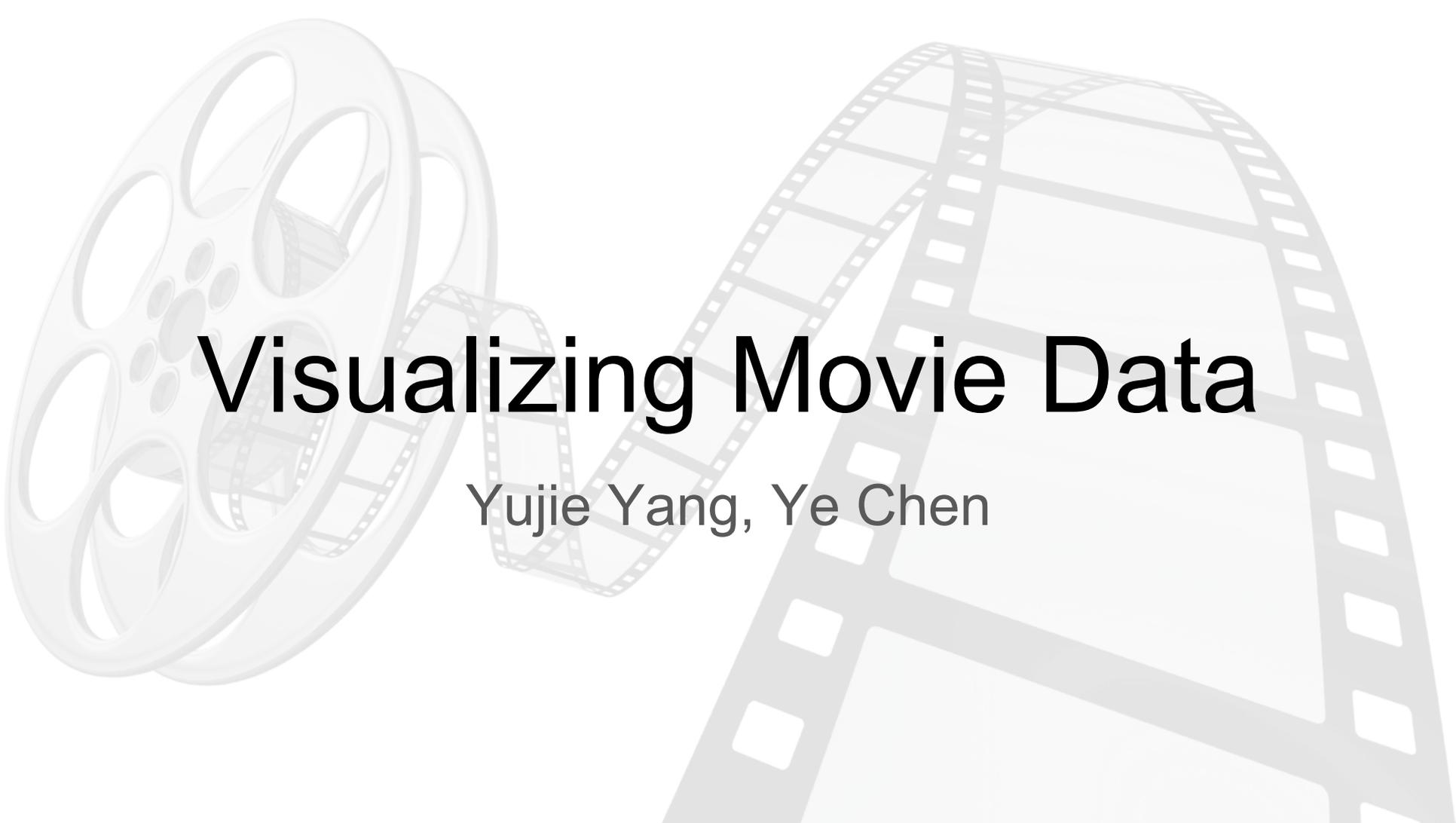
0

0.6%

List



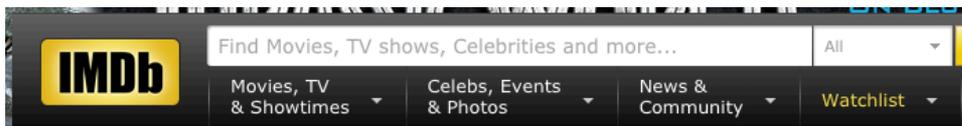
Desnethé-Missinippi-Churchill River
181 of 181 polls reporting
 NDP: Georgina Jolibois

The background features a large, light gray film reel on the left and a film strip on the right, both rendered in a semi-transparent, faded style. The film strip is curved and shows individual frames with sprocket holes.

Visualizing Movie Data

Yujie Yang, Ye Chen

Where?



IMDb Find Movies, TV shows, Celebrities and more... All

Movies, TV & Showtimes | Celebs, Events & Photos | News & Community | Watchlist



Harry Potter and the Deathly Hallows: Part 2 (2011) 193

12A | 130 min | Adventure, Drama, Fantasy | 15 July 2011 (UK)

Your rating: ★★★★★★★★ -/10
Ratings: **8.1**/10 from 483,604 users Metascore: 87/100
Reviews: 794 user | 464 critic | 41 from Metacritic.com

Harry, Ron and Hermione search for Voldemort's remaining Horcruxes in their effort to destroy the Dark Lord as the final battle rages on at Hogwarts.

Director: David Yates
Writers: Steve Kloves (screenplay), J.K. Rowling (novel)
Stars: Daniel Radcliffe, Emma Watson, Rupert Grint | [See full cast and crew »](#)

[+ Watchlist](#) [Watch Trailer](#) [Share...](#)

Contact the Filmmakers on IMDbPro »

Certificate: 12A | [See all certifications »](#)

Parents Guide: [View content advisory »](#)

Details

[Edit](#)

Official Sites: [Official Facebook](#) | [Official site](#) | [See more »](#)

Country: [USA](#) | [UK](#)

Language: [English](#)

Release Date: 15 July 2011 (UK) [See more »](#)

Also Known As: Harry Potter et les reliques de la mort: 2ème partie [See more »](#)

Filming Locations: [England, UK](#) [See more »](#)

Box Office

Budget: \$125,000,000 (estimated)

Opening Weekend: \$169,189,427 (USA) (15 July 2011)

Gross: \$380,955,619 (USA) (11 November 2011)

[See more »](#)

Company Credits

Production Co: [Warner Bros.](#), [Heyday Films](#), [Moving Picture Company \(MPC\)](#) [See more »](#)

Show detailed [company contact information](#) on [IMDbPro](#) »

Technical Specs

Runtime: 130 min

Sound Mix: [Dolby Digital](#) | [DTS](#) | [Dolby \(Dolby Surround 7.1\)](#) | [SDDS](#)

Color: [Color](#)

Aspect Ratio: 2.35 : 1

See [full technical specs](#) »

What?

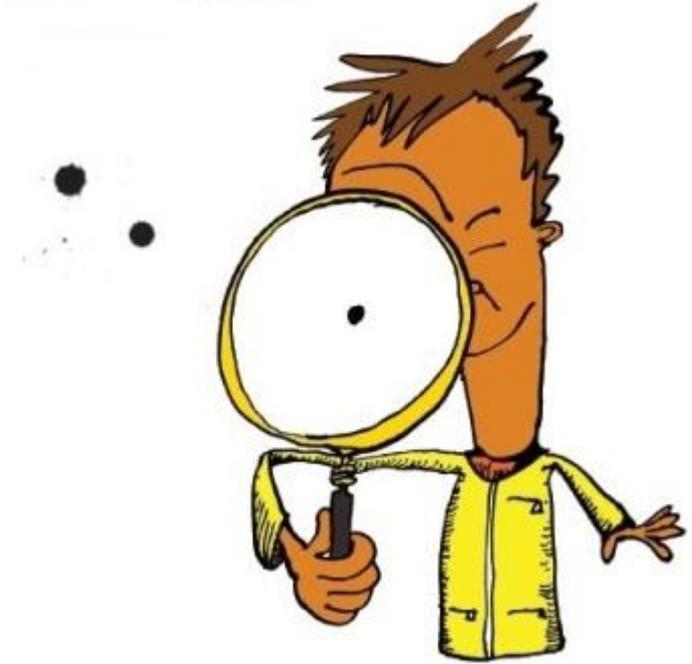
name	year	rate	runtime(mir)	genre	certificate	boxoffice	budget	opening_thea	release_date
Avatar (2009)	2009	7.9	162	Action Adventure Fantasy Sci-Fi	PG_13	761000000	\$237,000,000 (estimated)	3,452	18 December 2009 (Ca
The Dark Knight (2008)	2008	9	152	Action Crime Drama	PG_13	533000000	\$185,000,000 (estimated)	4,366	18 July 2008 (Canada
Pirates of the Caribbean: Dead Man's Chest (2006)	2006	7.3	151	Action Adventure Fantasy	PG_13	423000000	\$225,000,000 (estimated)	4,133	7 July 2006 (USA)
Toy Story 3 (2010)	2010	8.4	103	Animation Adventure Comedy Family Far	G	415000000	\$200,000,000 (estimated)	4,028	18 June 2010 (Canada
Transformers: Revenge of the Fallen (2009)	2009	6	150	Action Adventure Sci-Fi	PG_13	402000000	\$200,000,000 (estimated)	4,234	24 June 2009 (Canada
Harry Potter and the Deathly Hallows: Part 2 (2011)	2011	8.1	130	Adventure Fantasy Mystery	PG_13	381000000	\$125,000,000 (estimated)	4,375	15 July 2011 (Canada
Star Wars: Episode III - Revenge of the Sith (2005)	2005	7.7	140	Action Adventure Fantasy Sci-Fi	PG_13	380000000	\$113,000,000 (estimated)	3,661	19 May 2005 (Canada)
Transformers: Dark of the Moon (2011)	2011	6.3	154	Action Adventure Sci-Fi	PG_13	352000000	\$195,000,000 (estimated)	4,011	29 June 2011 (Canada
Spider-Man 3 (2007)	2007	6.2	139	Action Adventure	PG_13	337000000	\$258,000,000 (estimated)	4,252	4 May 2007 (Canada)
Alice in Wonderland (2010)	2010	6.5	108	Adventure Family Fantasy	PG	334000000	\$200,000,000 (estimated)	3,728	5 March 2010 (Canada
Shrek the Third (2007)	2007	6	93	Animation Adventure Comedy Family Far	PG	321000000	\$160,000,000 (estimated)	4,122	18 May 2007 (Canada)
Transformers (2007)	2007	7.2	144	Action Adventure Sci-Fi	PG_13	319000000	\$150,000,000 (estimated)	4,011	2 July 2007 (Canada)
Iron Man (2008)	2008	7.9	126	Action Adventure Sci-Fi	PG_13	318000000	\$140,000,000 (estimated)	4,105	2 May 2008 (Canada)
Indiana Jones and the Kingdom of the Crystal Skull (2007)	2008	6.2	122	Action Adventure	PG_13	317000000	\$185,000,000 (estimated)	4,260	22 May 2008 (Canada)
Iron Man 2 (2010)	2010	7.1	124	Action Adventure Sci-Fi	PG_13	312000000	\$200,000,000 (estimated)	4,380	7 May 2010 (Canada)
Pirates of the Caribbean: At World's End (2007)	2007	7.1	169	Action Adventure Fantasy	PG_13	309000000	\$300,000,000 (estimated)	4,362	25 May 2007 (USA)
Harry Potter and the Half-Blood Prince (2009)	2009	7.5	153	Adventure Family Fantasy Mystery	PG	302000000	\$250,000,000 (estimated)	4,275	15 July 2009 (Canada)
The Twilight Saga: Eclipse (2010)	2010	4.9	124	Adventure Drama Fantasy Romance	PG_13	301000000	\$68,000,000 (estimated)	4,416	30 June 2010 (Canada)
The Twilight Saga: New Moon (2009)	2009	4.6	130	Adventure Drama Fantasy Romance	PG_13	297000000	\$50,000,000 (estimated)	4,024	20 November 2009 (Ca
Harry Potter and the Deathly Hallows: Part 1 (2010)	2010	7.7	146	Adventure Family Fantasy Mystery	PG_13	295000000	\$150,000,000 (estimated)	4,125	19 November 2010 (Ca
Up (2009)	2009	8.3	96	Animation Adventure Comedy Family	PG	293000000	\$175,000,000 (estimated)	3,766	29 May 2009 (Canada)
Inception (2010)	2010	8.8	148	Action Mystery Sci-Fi Thriller	PG_13	293000000	\$160,000,000 (estimated)	3,792	16 July 2010 (Canada)
The Chronicles of Narnia: The Lion, the Witch and the W	2005	6.9	143	Adventure Family Fantasy	UNRATED	292000000	\$180,000,000 (estimated)	3,616	9 December 2005 (Can
Harry Potter and the Order of the Phoenix (2007)	2007	7.4	138	Adventure Family Fantasy Mystery	PG_13	292000000	\$150,000,000 (estimated)	4,181	11 July 2007 (Canada)
Harry Potter and the Goblet of Fire (2005)	2005	7.6	157	Adventure Family Fantasy Mystery	PG_13	290000000	\$150,000,000 (estimated)	3,858	18 November 2005 (Ca
The Twilight Saga: Breaking Dawn - Part 1 (2011)	2011	4.9	117	Adventure Drama Fantasy Romance	PG_13	281000000	\$110,000,000 (estimated)	4,066	18 November 2011 (Ca
The Hangover (2009)	2009	7.8	100	Comedy	UNRATED	277000000	\$35,000,000 (estimated)	3,269	5 June 2009 (Canada)
Star Trek (2009)	2009	8	127	Action Adventure Sci-Fi	PG_13	258000000	\$140,000,000 (estimated)	3,849	8 May 2009 (Canada)
I Am Legend (2007)	2007	7.2	101	Drama Sci-Fi Thriller	PG_13	256000000	\$150,000,000 (estimated)	3,606	14 December 2007 (Ca
The Blind Side (2009)	2009	7.7	129	Biography Drama Sport	PG_13	256000000	\$29,000,000 (estimated)	3,110	20 November 2009 (Ca
The Hangover Part II (2011)	2011	6.5	102	Comedy	R	254000000	\$80,000,000 (estimated)	3,615	26 May 2011 (Canada)
Despicable Me (2010)	2010	7.7	95	Animation Comedy Family	TV_PG	252000000	\$69,000,000 (estimated)	3,476	9 July 2010 (Canada)
Night at the Museum (2006)	2006	6.4	108	Action Adventure Comedy Family Fantas	PG	251000000	\$110,000,000 (estimated)	3,768	22 December 2006 (Ca
... (2006)	2006	7.0	117	Animation Adventure Comedy Family Sci-Fi	PG	244000000	\$120,000,000 (estimated)	3,287	6 July 2006 (Canada)

What?

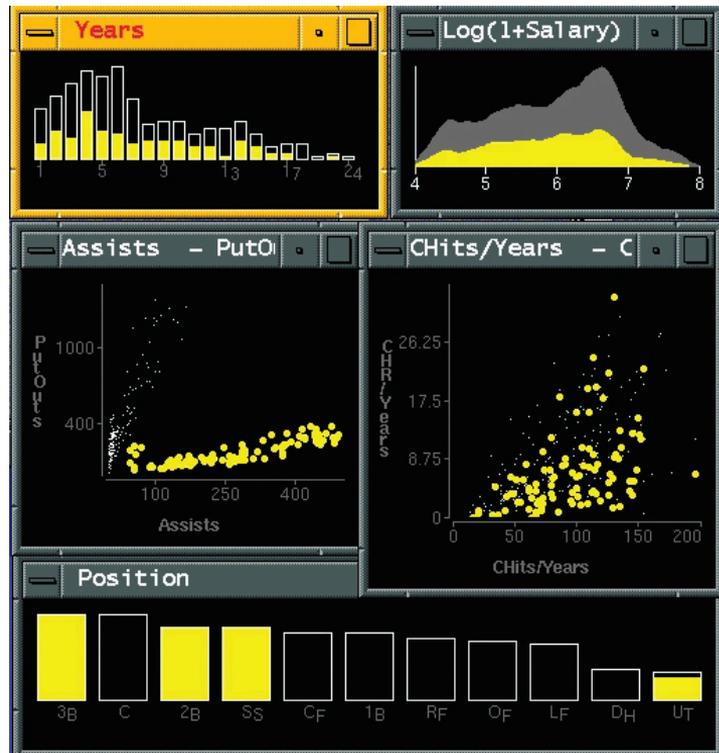
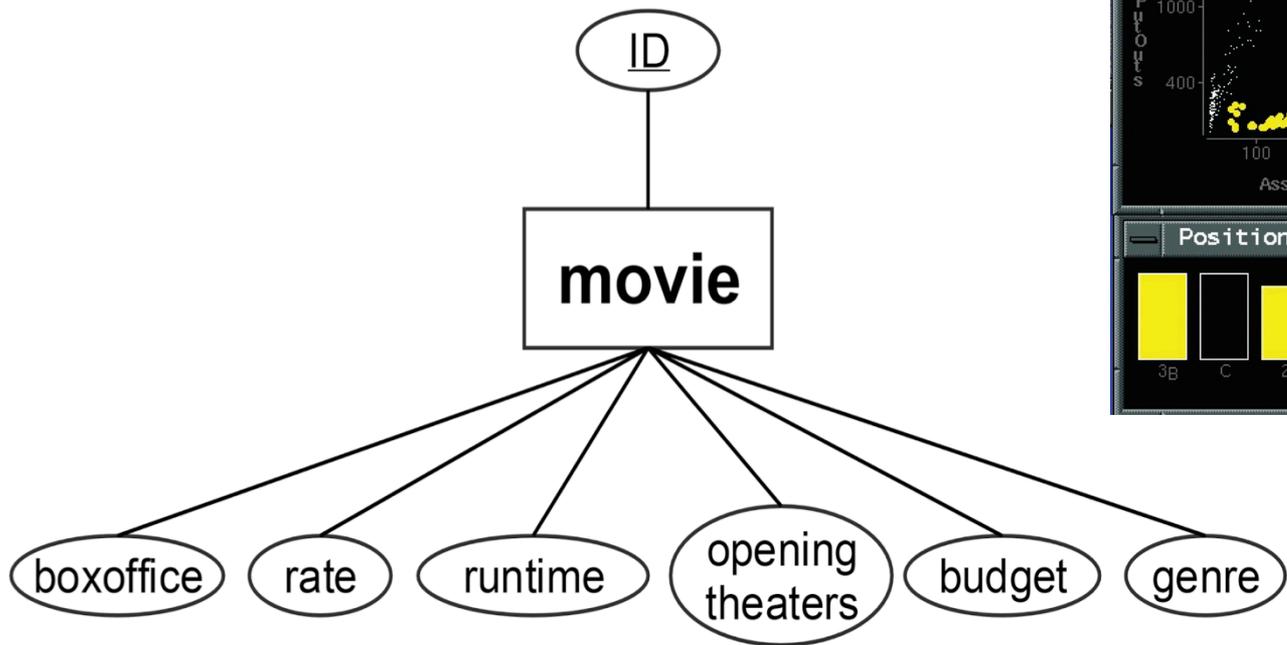
ID	Name	Boxoffice (USD)	Rate	Runtime (mins)	Opening Theaters	Budget	Release Date	Genre
47	Up	293000000	8.3	96	3766	175000000	May 2009	Animation Adventure Comedy Family

Why?

Explore the distribution of data.



How?

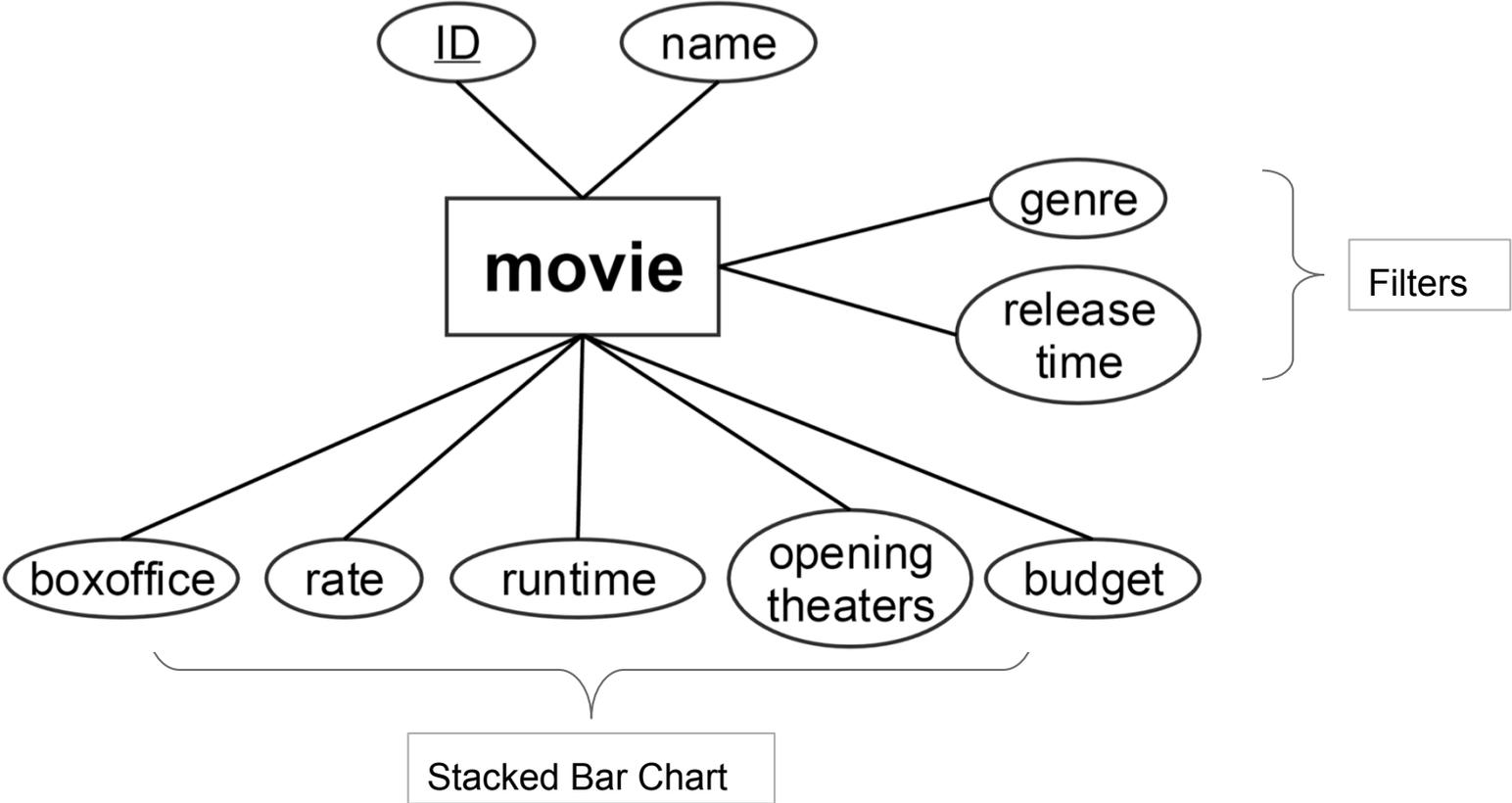


Why?

Help people to choose a movie.



How?



How?





Thanks

First Thought on

Exploratory Scholar Data

Zipeng Liu
Oct 22 2015

Dataset

- 2M papers, 8M citations
 - title, authors, affiliations, year, venue, abstract
- 1M authors, 4M co-authorships
 - name, affiliations, #papers, #citations, H-index, key terms...

Dataset

- 2M papers, 8M citations
 - title, authors, affiliations, year, venue, abstract
- 1M authors, 4M co-authorships
 - name, affiliations, #papers, #citations, H-index, key terms...

Networks

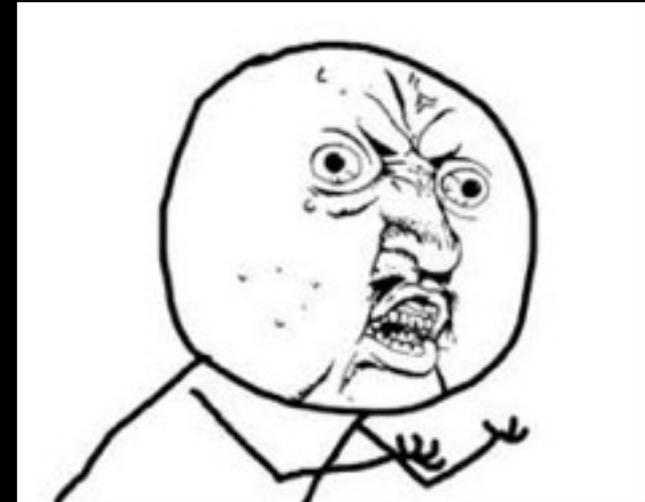
Dataset — Another Angle

- 2M papers, 8M citations
 - title, authors, affiliations, year, venue, abstract
- 1M authors, 4M co-authorships
 - name, affiliations, #papers, #citations, H-index, key terms...

Sets

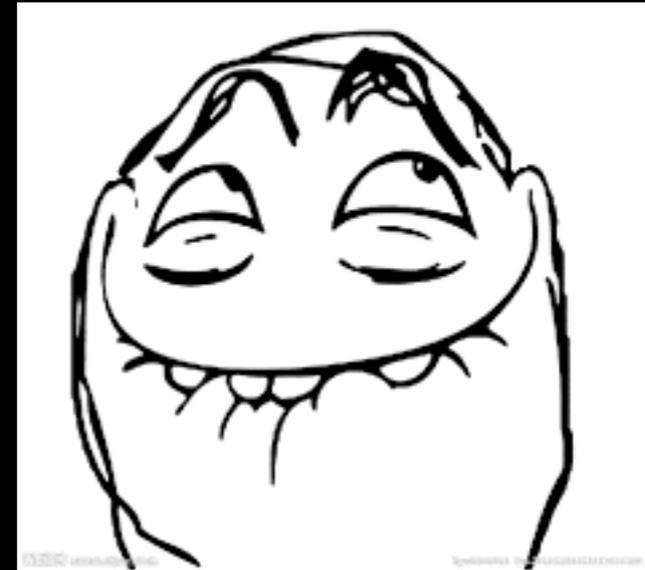
Dataset

- 2M papers, 8M citations
 - title, authors, affiliations, year, venue, abstract
- 1M authors, 4M co-authorships
 - name, affiliations, #papers, #citations, H-index, key terms...

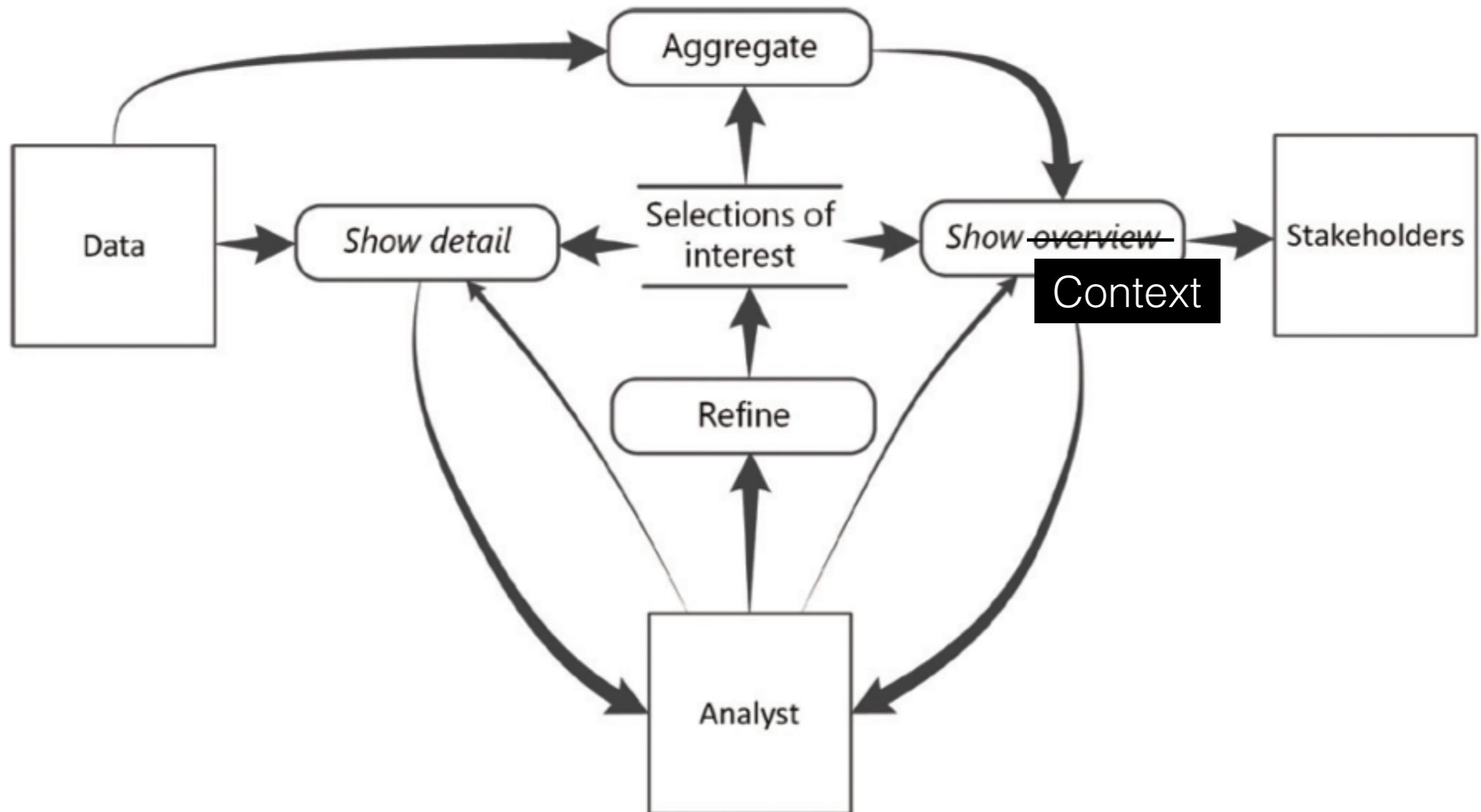


Goal?

- ~~Make sense of whole dataset~~
- Explore a paper, a topic, an author, a venue...



Detail to Overview (Context) via Selection and Aggregation



Thank you

Knomos

MAPPING A KNOWLEDGE NETWORK OF LAW

Visual navigation platform for big data
research and collaboration in the legal industry

Law is Stuck

Legal research is constrained by:
High search costs
Decentralized sources
Institutional barriers



Outdated Content Format
Text-heavy, Static, and Linear



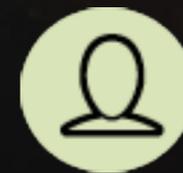
Duplicate Search Costs
Firm Work Product Silo



High Client Costs
Limited Access to Justice



Content Barriers
Private Content Paywall



Solitary Search
No Collective User Activity



Enhanced Legal Research Software

KNOMOS Capital Cost

Legend Related Comments

- Laws & Regulations**
 - Income Tax Act (CDN)
 - s. 20(1)(gg)
 - Excise Tax Act (CDN)
 - s. 172.1(1)
 - Financial Corporations Capital Tax Act (RSNL)
 - s. 2(n)
 - Financial Corporations Capital Tax Act (SNB)
 - s. 1(b)(ii)
- Cases & Rulings**
 - Supreme Court (42)**
 - Imperial Oil Ltd. v. Canada [2006 SCC 46](#)
 - Ludco Enterprises Ltd. v. Canada [2001 SCC 62](#)
 - [...]
 - Federal Court of Appeal (45)**
 - Imperial Oil Ltd. v. Canada [2004 FCA 361](#)
 - Novopharm Ltd. v. Canada [2003 SCC 62](#)
- Resources**

KNOMOS Hearsay

Level 1 > Level 2 > Current

Search Term: Hearsay

Legend Results Related Comments

Results (31)

Title Matches (2)

- §5.06 - Hearsay**
Criminal Procedure > Ch. 5 > Evidence > §5.06
- 5. Documents as Hearsay - Statutory Exceptions**
Criminal Procedure > Ch. 5 > Evidence > §5.06 Hearsay > 5

Text Matches (29)

- §3.03 - 2. Content**
Criminal Procedure > Ch 3 - Preparation for Trial > §3.03 > 2.
[...] The accused and defence counsel are entitled to inspect any documents that the Crown will produce under the business records exception to the hearsay rule (s. 30(7) of the Canada Evidence Act).
- §3.22 - Witness and Client Statements**
Criminal Procedure > Ch 3 - Preparation for Trial > §3.22
[...] Statements made by a witness who later recants at trial, may themselves be given in evidence and used for the truth of those statements as exceptions to the hearsay rule - see the discussion in Chapter 5

Team

History of industry leading software design applied to a unique visual platform for legal data research & collaboration



Core Team

Adam La France (CEO)

James Abney (CTO)

Jesse Abney (COO)

Craig McInnes (Systems Design)



Key Partners



Knomos

Why Knomos?

Legal Research Usability Problems

User Driven Design

Networked Data: BCLaws & CanLII APIs

Choice of D3 Vis Idioms

Established Full Tech Stack w/ Room to Extend

