RoboVis

Alistair Wick

EvoArm

- Small robot arm
- 3 degrees of freedom
- 3D printable
- Controlled with a Python App
- ... where to go from here?



Customization!

- Every 3D-printed arm can be different
- Change mechanics for different purposes







Exploring Possible Configs



Changing one of dozens of parameters

- Tedious and impractical to try many designs
- Different people need different capabilities
- Can the exploration process be made accessible?



Vis can help!

Vis Idea

- Interactive exploration of design space
- O Data: Calculated online
 - O Reachable points
 - Max load (across reachable space)
 - Max velocity (across reachable space)
- O Design:
 - Spatial data -> spatial display?
 - Derive attributes?
 - Combine certain parameters?



Length 1



120N 110N 100N 90N 80N



PITCH: VISUALIZING THE ENERGY PERFORMANCE OF A BUILDING

ARASH SHADKAM



- ENERGY PERFORMANCE DATA OF A BUILDING (FOR NOW THE BUILDING IS THE CENTER FOR INTERACTIVE RESEARCH ON SUSTAINABILITY/"CIRS")
- TIME-SERIES DATA FROM SENSORS INCLUDING TEMPERATURE AND OCCUPANCY DATA (IF POSSIBLE)
- DERIVED: NORMALIZED ENERGY PERFORMANCE DATA



- BETTER UNDERSTANDING OF THE BUILDING'S ENERGY PERFORMANCE
- DISCOVERING TRENDS AND CORRELATIONS IN THE ENERGY PERFORMANCE DATA AND
 IDENTIFY POTENTIAL OPTIMIZATION OPPORTUNITIES IN THE BUILDING'S PERFORMANCE

HOW

0

Ø

Walkability

0

MIT Campus Example Data - C	Central Square, Cam	bridge MA			Change File Browse	Home
	Bar Chart / Ene	ərgy				
(<u>umi</u>)	Building B	Energy				
dashboard			Annual Consumption	Cooling Heating Lighting	ng Equipment	=
Project Information	25M				ng Equipment	
Number of Buildings: 113 Number of Use Types: 5 Area Range: 459 - 43,664 sqm	20M					
Chart Type	sumption				الر.	
Scorecard	G 10M					
Building Columns	Energ					
Use Type Columns	5M					
Scatter Plot						11
Building Map	om جو چې	20 20 20 20 20 20 20 20 20 20 20 20 20 2	0 12 10 10 10 10 10 10 10 10 10 10 10 10 10			2.00 2.00
Chart Options	no no	5. 4	Building Names	4. 4.		
Sort ↓	lcon	Category	Value	Range	Unit	
Y Axis - OE	Ø	Energy	2590825	150684-22013637	KwH	

35

km

9-43

0





- FACET: MULTI-FORM OVERVIEW-DETAIL VIEWS/LINKED HIGHLIGHTING
- MANIPULATE: SELECT
- REDUCE: FILTER/RANGE SLIDERS FOR DIFFERENT TIME SPANS







THANKS!





A VISUALIZATION TOOL FOR COMPUTER PROGRAM PERFORMANCE DEBUGGING

Augustine Wong

WHAT IS COMPUTER PROGRAM PERFORMANCE DEBUGGING?

Diagnosing why a computer program is running slowly





HOW DO VISUALIZATION TOOLS HELP?

Let's look at an existing visualization tool...





PROJECT OBJECTIVES

Create a visualization tool which:



- Uses the "search, show context, expand on demand" approach
- Visualizes "patterns" of computer program behavior
- Evaluates which patterns are good starting points for initially exploring the computer program

Quantum Annealing Visualization

Austin Wallace 5th year undergraduate student Integrated Science-Machine Learning



Chimera Graph

IQBit

Visualizations For Justifying Machine Learning Predictions

David Johnson

Motivation

- Strengths of ML allowed expansion to diverse fields
- Fields and contexts far removed from traditional ML
- Users not trained in ML

Motivation

Biggest factor for users is understanding how predictions occur

Particularly important in¹:

- High risk applications like medicine
- Consumer-facing applications such as Recommender Systems
- Context-Aware applications

¹ Biran, McKeown. 2014. Justification Narratives For Individual Classification

Justification Visualization

Visualizations present important evidence for a prediction

Intensions are to tie in to thesis work



Dilan Ustek Matthew Chun

Motivation

- Target User: Yelp end-users
- Comparing businesses
- Filtered visualization

Busi	nesse	s > F	Restaurar	nts						
Ameri Asian Break More	can (Tra Fusion fast & B categoi	aditional) runch ries	Bu Ca Ch	irgers ifes inese	Delis Fast Food Indian	Italian Japanese Mediterranean		Noodles Pizza Sandwiches	Sea Sus Viet	food hi Bars namese
\$	\$\$	\$\$\$	\$\$\$\$	(S Open Now	Make a Reservation	Good for Lunch	Good	for Groups	2. All Filters	
	_				11			< Mo' Map	Redo search	when map moved
			Les Fa	ux Bourgeois	Mount Ple 663 E 15t	asant h Avenue	0	< Mo' Map	Redo search	when map moved
	S	Ad SS	Les Fa	ux Bourgeois 298 reviews h, Cafes	Mount Ple 663 E 15t Vancouve Canada (604) 873	asant h Avenue r, BC V5T 2R6 -9733	0	< Mo' Map + -	Redo search	when map moved
	Vibrant	t and con	Les Fa	ux Bourgeois 298 reviews h, Cafes h the heart of East Va r makes you pine for	Mount Pie 663 E 15t Vancouve Canada (604) 873 an - Classic Bistro Fare, mode Paris, or transport you, mode	asant h Avenue r, BC V5T 2R6 -9733 rately priced and faithfu d more	(i) ul to	< Mo' Map + -	Redo search	when map mo North Vancouver

463 W 8th Avenue Vancouver, BC V5Y 3Z5

Map data @2017 Google Terms of Use

Ads by Google

Canada (778) 379-5344

POKE EVERYWHERE! Why now? Well, Vancouver is always kind of late in the hottest culinary trends, but even though a bit late as usual, this poke thing really seems to have caught on...

40 reviews

\$\$ · Live/Raw Food, Hawaiian

read more

The Dataset

https://www.yelp.com/dataset_challenge/dataset

yelp_academic_dataset_business.json

```
"business_id": "encrypted business id",
"name": "business name".
"neighborhood": "hood name".
"address":"full address",
"city":"city",
"state": "state -- if applicable --".
"postal code": "postal code".
"latitude":latitude,
"longitude":longitude,
"stars":star rating, rounded to half-stars,
"review_count":number of reviews.
"is_open":0/1 (closed/open).
"attributes":["an array of strings: each array element is an attribute"],
"categories":["an array of strings of business categories"],
"hours":["an array of strings of business hours"],
"type": "business"
```

yelp_academic_dataset_user.json

"user_id": "encrypted user id". "name": "first name". "review_count":number of reviews. "velping_since": date formatted like "2009-12-19". "friends":["an array of encrypted ids of friends"]. "useful": "number of useful votes sent by the user", "funny": "number of funny votes sent by the user". "cool": "number of cool votes sent by the user". "fans": "number of fans the user has". "elite":["an array of years the user was elite"]. "average_stars":floating point average like 4.31, "compliment hot":number of hot compliments received by the user. "compliment_more":number of more compliments received by the user, "compliment_profile": number of profile compliments received by the user, "compliment_cute": number of cute compliments received by the user, "compliment_list": number of list compliments received by the user, "compliment_note": number of note compliments received by the user, "compliment_plain": number of plain compliments received by the user, "compliment_cool": number of cool compliments received by the user, "compliment_funny": number of funny compliments received by the user, "compliment_writer": number of writer compliments received by the user, "compliment_photos": number of photo compliments received by the user, "type": "user"

Scope

- One city but yet to be decided
- Focus on the end users, aka the people who use the Yelp site/app
- Data features to consider ... it depends but theme of holistic/detailed comparison
 - Discover the "nuances" behind the existing Yelp data eg. distribution of 5 star restaurants in different price categories
 - More informed decisions for end users

Project Pitch

Information Visualization 2017 Felix Grund

Munich





Your consultants, developers and troubleshooters



Do you need advice regarding your current IT solution or targeted assistance for a specific project? Our experienced consultants uncover the optimisation potential of your existing strategy and cater to your individual needs. We offer Requirements Engineering, UI/UX Consulting, Project Management and Cloud Strategy from a single source.

EXACTLY WHAT I NEED



Who is Scandio?

- 2016:
 - 40 employees
 - 82 clients
 - 176 projects
- Projects:



- Fixed price ("client pays what's estimated")
- Time and material ("client pays the hours")

What is a fixed price project at Scandio?

- Efforts range from 5 days 100 days
- Duration ranges from 3 weeks 1 year
- Before project starts: effort estimation
- Generally higher risk of "failure"
 - If over estimation in the end, company mostly has to pay (sometimes compromises with client)



What are the project results?

- Total amount of efforts in the end
 - Exactly as estimated (rare)
 - Less than estimated (sometimes) \odot
 - More than estimated (sometimes) 🟵



What are the key attributes?

- 1. Hours worked
 - Employees track time on project in web app
- 2. Degree of completion (DOC)
 - Estimated monthly by project lead
- 3. Hourly rate for project
 - Determined in the beginning dependent on budget and total effort
 - Changes retrospectively depending on 1 and 2




? Questions ?



- When do estimation and degree of completion conflict?
- When are our hourly rates too low?
- How do hourly rates change retrospectively?
- What tendencies can we observe over multiple projects?
- When interfere to maintain project success?
- How can we identify wrong estimations on DOC?
- How do project leads differ in their monthly estimations?



Is there still time?

Time Tracking

Tages-Informationen						
Datum 13.05.2014	von 09:45	bis 17:30	Pause 0,75	Stunden 7,00		
Buchungs-Informati	onen					
Projektkennung	Tätigkeit	Issue ID	Bemerkung	Stunden		
DKMS_OPT1	Dashboard	DKMSSUPP 95	-Dashboard Anpassungen	1,00		
DKMS_OPT1	Dashboard	DKMSSUPP 96	-Dashboard styling	0,75		
DKMS_OPT1	News-Umstrukturierung	DKMSSUPP 102	-News Styling	1,25		
BSH_SUPP2014	PIWIK Support	BSHP-22	Test System Sync	0,50		
BSH_SUPP2014	Corporate Wiki Support	BSHSUPP- 226	Test Upgrade	0,25		
INF_SEC2014	POC - User Switch	INFPRJ-18	DiskussionenTests/Implementierung Tomcat Proxy	1,00		
DKMS_OPT1	TPL		Telko mit Guido zu Projektstand	1,00		
DKMS_OPT1	Dashboard	DKMSSUPP 119	-Dashboard Performance	1,25		

Project results (good)

Mitarbeiterstunden

Mitarbeiter	Stunden
fgrund	60,00
gschmidl	12,50
Summe	72,50

Projektstunden

Tätigkeit	Plan	Ist	Rest
DKMS_OPT1: Blogposts-Plugin	16,00	14,75	1,25
DKMS_OPT1: Dashboard	16,00	15,25	0,75
DKMS_OPT1: IE10 Anpassungen	8,00	2,75	5,25
DKMS_OPT1: News-Migration	8,00	0,75	7,25
DKMS_OPT1: News-Umstrukturieru	8,00	0,25	-2,25
DKMS_OPT1: Patient Faces	24,00	11,	12,75
DKMS_OPT1: TPL	4,00	17,-	-13,50
Summe	84,00	72,50	11,50

Project results (bad)

Mitarbeiterstunden

Mitarbeiter	Stunden
fgrund	52,00
jgrabski	10,75
jstadler	9,00
Summe	71,75

Projektstunden		<u>\</u>		
Tätigkeit	Plan	lst	R	est
DKMS_SSO: SSO Link	0,00	14,2		-14,25
DKMS_SSO: SSO Plugin	32,00	57,50		-25,50
Summe	32,00	71,75	5	-39,75

Thanks.

Visualizing Internal Components of a **Convolutional Neural** Network

Mahdi Ghodsi - Hooman Shariati

Background:

What is Machine Learning

Machine Learning is taking over.

Applied to many fields: Bioinformatics, Gaming, Medical diagnosis, Marketing, Machine Vision,





The idea has been around since 1980s But Introduction of GPU computing with 30x speed up gave DNNs a boost





Google Deep Dream

ImageNet Competition

Very Popular Research Area

Cited by 160 Related articles All 7 versions Cite Save More

Google	deep neural network		convolutional neural net	
Scholar	About 1,200,000 results (0.08 sec)	My Citations	About 28,800 results (0.10 sec)	If My Citations
Articles Case law My library	Multi-column deep neural network for traffic sign classification <u>D CireşAn</u> , U Meier, <u>J Masci</u> , <u>J Schmidhuber</u> - Neural Networks, 2012 - Eisevier We describe the approach that won the final phase of the German traffic sign recognition benchmark. Our method is the only one that achieved a better-than-human recognition rate of 99.46%. We use a fast, fully parameterizable GPU implementation of a Deep Neural Cited by 243 Related articles All 22 versions Web of Science: 94 Cite Save More	[PDF] yimg.com UBC eLink	Imagenet classification with deep convolutional neural networks <u>A Krizhevsky</u> , <u>I Sutskever</u> , <u>GE Hinton</u> - Advances in neural, 2012 - papers.nips.cc Abstract We trained a large, deep convolutional neural network to classify the 1.3 million high-resolution images in the LSVRC-2010 ImageNet training set into the 1000 different classes. On the test data, we achieved top-1 and top-5 error rates of 39.7% and 18.9% Cited by 9657 Related articles All 97 versions Cite Save More	[PDF] nips.cc
Any time Since 2017 Since 2016 Since 2013 Custom range	New types of deep neural network learning for speech recognition and related applications: An overview <u>Leng, G.Hinton, B.Kingsbury</u> - Acoustics, Speech and Signal, 2013 - ieeexplore.ieee.org Abstract: In this paper, we provide an overview of the invited and contributed papers presented at the special session at ICASSP-2013, entitled "New Types of Deep Neural Network Learning for Speech Recognition and Related Applications," as organized by the Cited by 186 Related articles A II13 versions Cite Save More	[PDF] psu.edu UBC eLink	Large-scale video classification with convolutional neural networks <u>A Karpathy, G Toderici</u> , S Shetty, <u>T Leung</u> Proceedings of the, 2014 - cv-foundation.org Abstract Convolutional Neural Networks (CNNs) have been established as a powerful class of models for image recognition problems. Encouraged by these results, we provide an extensive empirical evaluation of CNNs on large-scale video classification using a new Cited by 820 Related articles All 20 versions Cite Save More	[PDF] cv-foundation.org
Sort by relevance Sort by date ✓ include patents ✓ include citations	IPPF) Scalable Minimum Bayes Risk Training of Deep Neural Network Acoustic Models Using Distributed Hessian-free Optimization. Bkingsbury, TN Sainath, H Soltau - Interspeech, 2012 - sites google.com Abstract Training neural network acoustic models with sequencediscriminative criteria, such as state-level minimum Bayes risk (sMBR), been shown to produce large improvements in performance over cross-entropy. However, because they entail the processing of lattices, Cited by 174 Related articles All 2 versions Cite Save More	(PDF) google.com	Face recognition: A convolutional neural-network approach <u>S Lawrence</u> , CL <u>Giles</u> , AC <u>Tsol</u> , on neural networks, 1997 - ieeexplore:ieee.org Abstract: We present a hybrid neural-network for human face recognition which compares favourably with other methods. The system combines local image sampling, a self- organizing map (SOM) neural network, and a convolutional neural network. The SOM Cited by 1352 Related articles All 23 versions. Web of Science: 354 Cite Save More <u>Convolutional neural networks</u> for sentance classification	(PDF) psu.edu UBC eLink
ĭ Create alert	KL-divergence regularized deep neural network adaptation for improved large vocabulary speech recognition <u>D'W, KYao, H Su</u> , G Li, F Seide - Acoustics, Speech and, 2013 - ieeexplore.ieee.org Abstract: We propose a novel regularized adaptation technique for context dependent deep neural network hidden Markov models (CD-DNN-HMM). The CD-DNN-HMM has a large output layer and many large hidden layers, each with thousands of neurons. The huge	[PDF] semanticscholar.org UBC eLink	Y Kim - arXiv preprint arXiv:1408.5882, 2014 - arXiv.org Abstract: We report on a series of experiments with convolutional neural networks (CNN) trained on top of pre-trained word vectors for sentence-level classification tasks. We show that a simple CNN with little hyperparameter tuning and static vectors achieves excellent Cited by 608 Related articles All 16 versions Cite Save	, , and og

However ...

How researchers see CNNs



"Neural networks have long been known as "black boxes" be- cause it is difficult to understand exactly how any particu- lar, trained neural network functions due to the large number of interacting, non-linear parts."

Yajin Zhou

Department of Computer Science North Carolina State University

How researchers see CNNs

How CNNs looks like



Visualizing and making sense of of CNNs in literature:

Visualizing and Understanding Convolutional Networks By M. Zeiler (NYU)





Visualizing Ambiguity

James Hicklin

Case Scenario

- Imagine you are Betty
- Just finished chemo for breast cancer
- Typical postchemo therapy is Tamoxifen for 5 years



Tamoxifen 10-year risk estimates compared to 5-year risk estimates (out of 1000)

Attribute		(Change	
Breast cancer recurrence	Ψ	28		
Death from breast cancer	$\mathbf{1}$	28		
Development of gallstones	1	2		
Development of endometrial cancer	1	16		
Stroke	1	2		

Point estimates...

 Imagine Betty only cared about her chance of dying from breast cancer and her chance of developing endometrial cancer



5-year vs. 10-year Tamoxifen Therapy

With confidence intervals...

5-year vs. 10-year Tamoxifen Therapy



Alternatives to Error Bars

Violin Plots



http://www.datavizcatalogue.com/methods/violin_plot.html

Box Plots



http://www.datavizcatalogue.com/methods/box_plot.html

Dynamic Icon Arrays

Benefits

About 1 out of 10 women improved their symptoms using this medicine.



Gradient Plots

Project

- Design new visualization to present ambiguity to patients
- Interactivity
 - Adjust bounds of error
 - Show best & worst case scenarios
 - Show how risk estimates might change given different samples

Dviz

$\bullet \bullet \bullet$

Visualizing Distributed Systems with Stewart Grant and Jodi Spacek

Motivation

- Understanding the behaviour of distributed systems is hard
- Developers need tools for comprehending their systems
- Most distributed systems are designed around FSM
- FSM are often how developers think of their systems
- Can an FSM be generated from an execution so developers can check their mental models?

Concept

- Collect distributed snapshots (state from across the whole system)
- Calculate a distance between each snapshot (xor distance)
- Plot each snapshot at it's relative distance using clustering
- Connect each snapshot with a time curve

etcd (distributed key value store) puts -> gets



Limitations

- States are not labeled meaningfully
- Semantics of state transitions are not clear
- FSM's require both

Extensions to Project

 $\bullet \bullet \bullet$

Improving Visualization

Interaction Extension

FSM would provide a higher level on which users could zoom in on





Proposed zoom

Filtering the Clusters

- Partitioning: intrinsic meaning
- Collect data invariants: filter to show aggregate data using existing tool set
- Label: Represent clusters by their invariants
- Visualize transitions: use the diff of cluster invariants

Research Questions

- Scatterplots? Occlusion? Continuous scatterplots?
- Interaction?
- Spatial aggregation? Does it make sense?
- Dimensionality reduction? Too much information?
- Effective color coding?
- Dimensional Ordering, Spacing, and Filtering Approach (DOSFA)? Similarities show patterns?

Why this project is neat

- Stems from an existing body of work
- Has practical applications for debugging distributed systems
- No end of data to represent, can easily be extended after the course

Visualizing patient clusters

Lovedeep Gondara

Problem

Physician researchers are often interested in data exploration before committing to a project.

Generally use descriptive statistics to see if there are any obvious signals.

Is there any specific group of patients that have the worse outcome compared to the rest?

Are there natural groupings in the dataset?

Is there an underlying structure to the data?

Proposed solution

Cluster visualization

Use dimensionality reduction methods such as t-sne.

Plot resulting clusters.

Draw survival plots by cluster membership.

Allow investigation of cluster membership.
Thanks

Spanner, Resurrected.

CPSC 547 Project Pitch

Madison Elliott February 16, 2017

Project originated as an MA thesis in the CS department

- Project originated as an MA thesis in the CS department
- New technique that applied lowstretch trees to network visualization

- Project originated as an MA thesis in the CS department
- New technique that applied lowstretch trees to network visualization
- Implemented novel edge-bundling technique

- Project originated as an MA thesis in the CS department
- New technique that applied lowstretch trees to network visualization
- Implemented novel edge-bundling technique
- Does not rely on fixed vertices/fixed layout or explicit hierarchical data structure

- Two iterations submitted for publication:
 - 1. Graph Drawing (technique focused)
 - 2. Pacific Vis (more emphasis on motivation and visualization application)

- Two iterations submitted for publication:
 - 1. Graph Drawing (technique focused)
 - 2. Pacific Vis (more emphasis on motivation and visualization application)
- Both rejected ⊗

- Two iterations submitted for publication:
 - 1. Graph Drawing (technique focused)
 - 2. Pacific Vis (more emphasis on motivation and visualization application)
- Both rejected 🟵
- Reviewer comments largely yearning for a deeper/more defined motivation

Resurrection Pitch

• Find the motivation!

Resurrection Pitch

• Find the motivation!

• Develop and execute a user study

Resurrection Pitch

• Find the motivation!

- Develop and execute a user study
- Revise and resubmit paper

• Lots of potential!



Figure 3: Comparison between an arbitrary spanning tree and a low-stretch spanning tree for an 8-by-8 grid graph.

• De-hairball a cluttered network:



• Novel, layout free network idioms:



Next Steps

• Complete literature review of network idioms, tasks and taxonomies

Next Steps

• Complete literature review of network idioms, tasks and taxonomies

 Brainstorm new cases where "set" or intuitive network layout is not optimal or necessary for a given task

Questions?

Automatic Grading Service Dataset

NICK BRADLEY

NBRAD11@CS.UBC.CA

Continuous grading service

5.5 GB from 13K test result records (more coming everyday)

Some data fields (don't worry if these don't mean anything to you)

- Grade for every commit each student made
- Test metrics: # tests pass/fail, coverage, duration
- Code metrics: LOC, build failures
- Grade requests: timestamp
- More data can be pulled from GitHub (diffs, history, branches,...)

Current Instructor Dashboard

Date	Repo	#Sec	% overall	% pass	% cover	#P	#F	#S	#LOC	Results
02/16 @ 04:40:53	cpsc310project_team40	12.0	72.8	66	95.89	33	17	0	316	eeeeeeeeeeeeeeeeeeeeeeeeeeeeeeeeeeeeee
02/16 @ 02:25:33	cpsc310project_team21	16.3	32.09	22	67.43	11	39	0	608	erefererererererererererererererererere
02/16 @ 01:33:41	cpsc310project_team80	9.2	44	30	95.84	15	35	0	505	efferenterenteren Efferenterenteren Ef
02/16 @ 01:17:14	cpsc310project_team194	10.6	32.28	22	68.4	11	39	0	250	efferererererererererererererererererer
02/16 @ 01:10:42	cpsc310project_team65	108.6	25.04	12	72.21	6	44	0	439	effere for the second s
02/16 @ 01:09:20	cpsc310project_team78	16.0	77.6	72	95.84	36	14	0	505	EEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEEE
02/16 @ 01:06:58	cpsc310project_team17	18.2	87.2	84	95.73	42	8	0	539	

Current Operational Dashboard



Idea + Impact

Student facing dashboard

- Expanded to CS110, CS210, and CS310 + their corresponding MOOC offerings
- Vis will be used by 1000s of students in production system
- Challenge: make it engaging + promote 'good' behaviour
- Feedback: prototype can be made available to current students

Instructor facing dashboard

- Design study with domain expert (current CPSC310 instructor)
- Challenge: needs to scale to 1000s of students

Analysis tool

- Probably only if you are interested in software engineering
- Likely end up as a SE paper

nbrad11@cs.ubc.ca

EMAIL

Visual Methods for Analyzing Motifs in Time-Oriented Data

Soheil Kianzad

PhD student CS

Stock technical analysis





www.aastocks.com/en/stock/detailchart.aspx?symbol=110000





Visualizing European soccer players

Yann Dubois

Other sports



World cup



https://www.datainnovation.org/2014/05/predicting-the-world-cup-winner-with-data-visualization/

By region



https://www.ibm.com/blogs/bluemix/2016/06/origins-of-soccer-superstars-part2/

By game



http://ieeexplore.ieee.org/stamp/stamp.jsp?arnumber=7042477

What?



- +25,000 matches
- +10,000 players
- 11 European leagues
- Players and Teams' attributes
- Detailed match events
- Betting odds

+ sports page scrapping

How?

- D3
- P5.js
- Tableau



GRADUATE STUDIES – DATA VISUALIZATIONS





WHO ARE WE?

- Responsible for academic oversight and support for approx. 300 graduate degree programs
- Strategic leaders in graduate education at UBC
- Support for faculty, programs & students
- Central hub for everything related to graduate students
 - Communications & Recruitment
 - Admission
 - Awards
 - Thesis & Dissertations
 - Doctoral Exams
 - Professional Development
- Approx. 10,000 graduate students in Vancouver



DATA PROJECTS

- Option 1: Canadian Graduate & Professional Student Survey (CGPSS)
 - Satisfaction levels in 13 sections, e.g. general, PD, research experience, financial support, social life
 - Breakdown by discipline, year of study, degree level, gender, etc.
- Option 2: Graduate School data
 - Application data
 - Enrolment statistics
 - Graduation statistics
 - Time in program and completion rates



CGPSS

	2010	2013	2016	Total
Doctoral	13 812	18 377	18 822	51 011
Research Masters	13 593	17 546	18 086	49 225
Other Masters	11 213	15 741	16 834	43 788
Total	38 618	51 664	53 742	144 024
univ	38	48	50	



CGPSS

Desired Outcomes:

- 1. Visualize key findings from 2016 study
- 2. Time comparison: 2010 to 2013 to 2016
- 3. Benchmarking: program vs. UBC vs. Canada

Audiences:

- Students
- Units (access controlled), e.g. program or department dashboard
 - Department Head
 - Program Director
 - Faculty


GRADUATE SCHOOL DATA (CURRENT)

REGISTRATION PERIOD (EXTRACT DATE)	APPLICATIONS	OFFERS	ACCEPTS (CAME)
<u>1995 (March-01-1996)</u>	7,411	2,793	1,732
<u>1996 (March-01-1997)</u>	7,301	2,892	1,821
<u>1997 (March-01-1998)</u>	7,592	2,885	1,786
<u>1998 (March-01-1999)</u>	6,864	2,879	1,826
<u>1999 (March-01-2000)</u>	7,550	3,278	2,074
2000 (March-01-2001)	7,420	3,207	2,066
2001 (March-01-2002)	7,899	3,305	2,156
2002 (March-01-2003)	10,170	3,841	2,548
2003 (March-01-2004)	11,778	3,989	2,728
2004 (March-01-2005)	10,339	4,090	2,802
2005 (March-01-2006)	9,729	3,933	2,671
2006 (March-01-2007)	9,935	4,069	2,690
2007 (March-01-2008)	9,720	4,042	2,672
2008 (March-01-2009)	9,859	4,378	2,907
2009 (March-01-2010)	11,767	4,810	3,363







GRADUATE SCHOOL DATA (CURRENT)



GRADUATE SCHOOL DATA (ALTERNATIVE EXAMPLE)



The University of Michigan offers a remarkably broad and rigorous array of graduate degree programs that are among the very best in the country in each field of study. The U-M attracts outstanding students to graduate study, and prepares them to make lasting contributions to society through successful careers in professions and academic disciplines, interdisciplinary study and joint degrees are a special strength of U-M's programs. The vibrant community of graduate and professional students on campus is highly diverse in obtanship, demographic background, and intellectual perspective. The Rackham Graduate School works together with faculty in the schools and colleges of the University to sustain this diversity, understanding it as critical to our dynamic intellectual climate.

In order to make the activity and culture of graduate programs more visible, we provide basic statistics about the Ph.D. programs at the University of Michigan. The data and variables were selected to offer a more accurate and helpful picture than those provided by external sources. We also encourage you to visit specific graduate program websites to learn more about the intellectual life, successes, and opportunities in each of our Ph.D. programs.



TEAM



Systems and Data Analysis Manager

Jens Locher

Assistant Dean





Visualizing Trends in Product Recommendations

Q.I. Leap Analytics

Who are we?

Q.I. Leap Analytics

- Team of data scientists
- Solutions for retail stores
- 2 products
 - Recommender System
 - Interactive Dashboard



What is a recommender system?

amazon	Amazon Video +		Q Valentine's Day deals XO
Departments - Amazon Video Originals	Prime + Video + Music + TV Shows Movies	Help Sell Gift Cards & Registry	Hello. Sign in Account & Lists - Cart Your Watchlist Your Vdeo Library Settings Getting Started Help
	Inside Out (Theatrical) 2015 C Image: Solution of the solution	h the transition. Joy, Fear, Anger, Disgust rough unfamiliar places to get back home.	STARZ Included with STARZ on Amazon for \$8.99/month after trial Watch with STARZ Start your 7-day free trial Prefer to buy? Buy Movie HD \$19.99 More Purchase Options Add to Watchlist
	Share 🔤 📑 🔰 👰		Send us Feedback Get Help

By placing your order or clicking "Watch Now", you agree to our Terms of Use. Sold by Amazon Digital Services LLC. Additional taxes may apply.

Customers Who Watched This Item Also Watched



What's the visualization task?

End user: Business that is using the Recommender System

End user desires:

- Which items recommended
- Trends in item recommendations
- Cluster users with similar purchase history
- Cluster items with similar buying history



What kind of data would you have to work with?

Transaction data for online store

- 50,000 transactions
- 2,000 unique items
- 13,000 unique customers
- With time, date, city of purchase

Generated recommendation data

- Customer, item viewing history, top 10 recommended items (with scores)





Benefits beyond the classroom

- Implemented in our dashboard product so customers would get to see how their recommender system is being used
- Possibility of internship on completion of project

- Talk to me afterwards if interested in the project!

