# Not a piece of cake: 
# Lexical Composition and Implicit Information

**Vered Shwartz**

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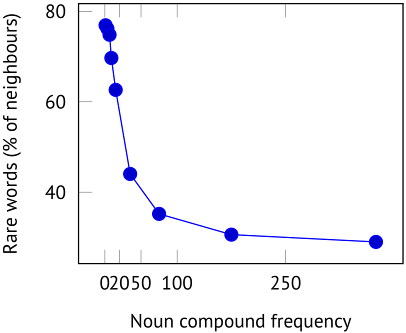
AI2

PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

# How to obtain meaningful phrase representations?

# Distributional Representations

## Distributional embeddings of rare terms are of low quality




| *syndicate representative* |
| --- |
| geloios |
| t.franse |
| adopter(s |
| ahchie |
| anquish |

Similar observations for adjective-noun compositions [Boleda et al., 2013].


COMPOSE
ALL THE WORDS!
imgflip.com

Let me do it for you!

# In this talk

1. How well do contextualized embeddings represent phrases?

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3. How to reveal implicit noun compound relations?

**Still a Pain in the Neck: Evaluating Text Representations on Lexical Composition.** Vered Shwartz and Ido Dagan. TACL 2019

# Issues with compositional representations

$$\mathbf{f}\left(\boxed{\vec{v}_{w_1}}, \boxed{\vec{v}_{w_2}}, \ldots, \boxed{\vec{v}_{w_k}}\right)$$

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$$\mathbf{f}\left( \boxed{\vec{v}_{w_1}}, \boxed{\vec{v}_{w_2}}, \ldots, \boxed{\vec{v}_{w_k}} \right)$$

"The whole is greater than the sum of its parts"

# Issues with compositional representations

$$\mathbf{f}\left( \vec{v}_{w_1}, \vec{v}_{w_2}, \ldots, \vec{v}_{w_k} \right)$$

"The whole is greater than the sum of its parts"

1. Meaning shift
2. Implicit meaning

# Meaning Shift

A constituent word may be used in a non-literal way

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A constituent word may be used in a non-literal way


VPC meanings differ from their verbs' meanings

# Implicit Meaning

Noun compounds

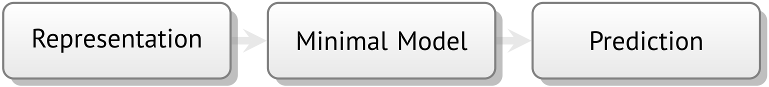
# Implicit Meaning

Adjective-noun compositions

Noun compounds

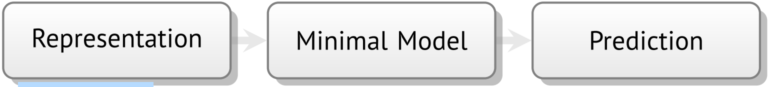

# Can existing representations address these phenomena?
## Probing Tasks

Simple tasks designed to test a single linguistic property [Adi et al., 2017, Conneau et al., 2018]



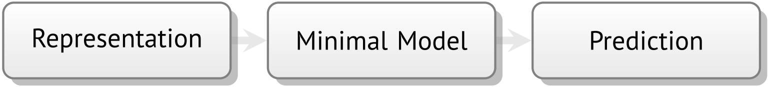
# Probing Tasks
## Representations

Standard / Contextualized




word2vec
GloVe
fastText
ELMo
GPT
BERT

# Probing Tasks
## Classifiers




1. Embed
2. Encode
3. Predict

# Classifiers

1. **Embed**: each representation
2. **Encode**: none / biLSTM / self-attention
3. **Predict**:

   $\vec{x}$ = vector of target span, additional inputs
   $\vec{o} = softmax(W \cdot ReLU(dropout(h(\vec{x}))))$

# Probing Tasks
## Tasks

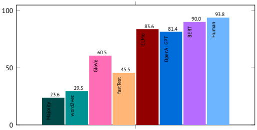
Meaning shift / Implicit meaning

Representation → Minimal Model → Prediction

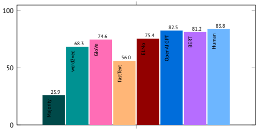
- VPC Classification
- LVC Classification
- NC Literality
- NC Relation
- AN Relation
- Phrase Type

# Tasks and Results

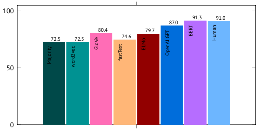
Verb-particle Classification



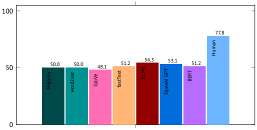

Light-Verb Construction



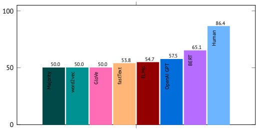

Noun Compound Literality




Noun Compound Relations




Adjective-Noun Attributes




(1) Meaning shift - human-like performance for contextualized
(2) Implicit meaning - far from humans

# Meaning Shift Tasks

# Verb-Particle Classification

## Task Definition

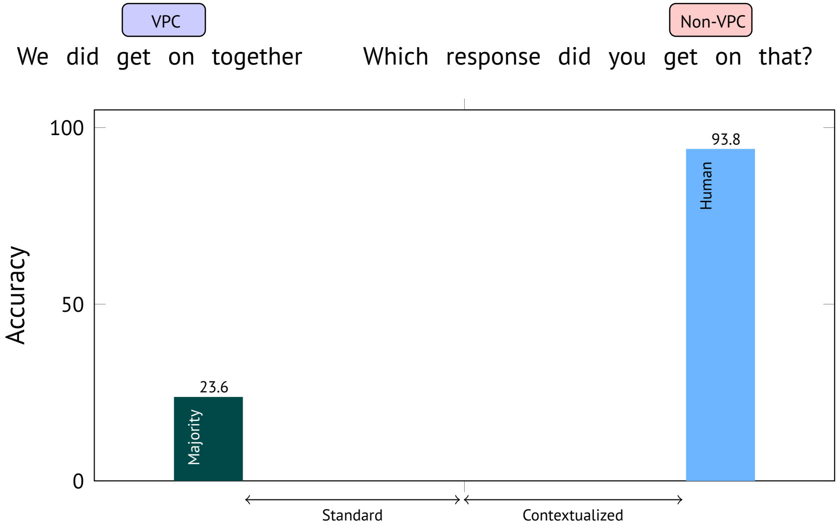
VPC

We did get on together

Non-VPC

Which response did you get on that?

# Results



VPC
Non-VPC
We did get on together
Which response did you get on that?
100
50
0
Accuracy
23.6
Majority
93.8
Human
Standard
Contextualized

# Results

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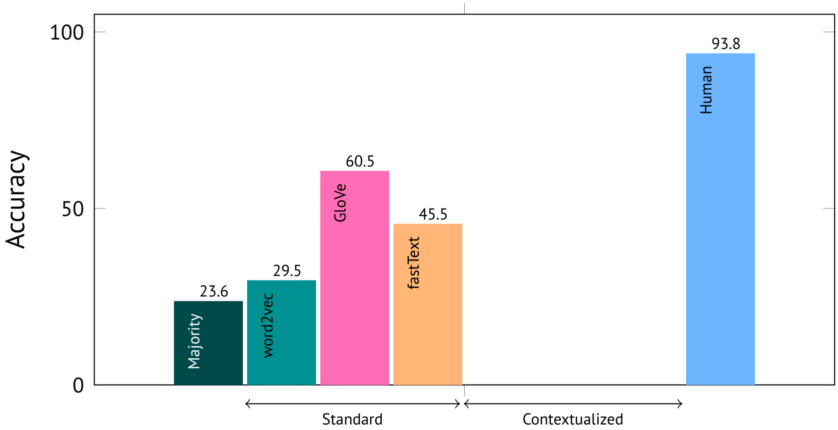
Non-VPC

Which response did you get on that?



# Results

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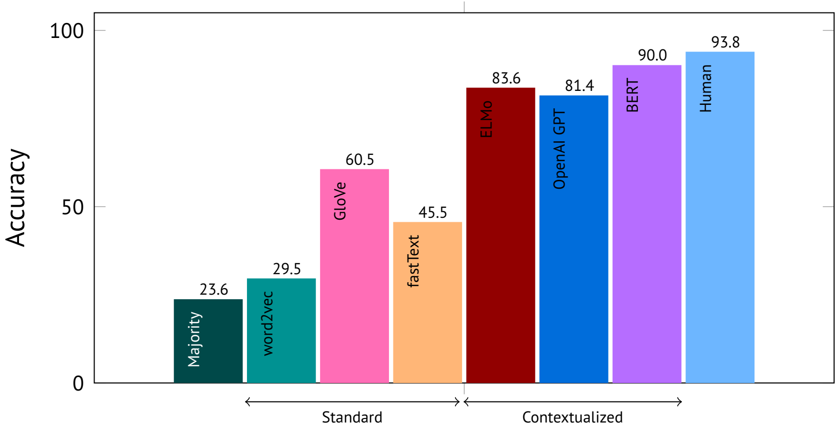
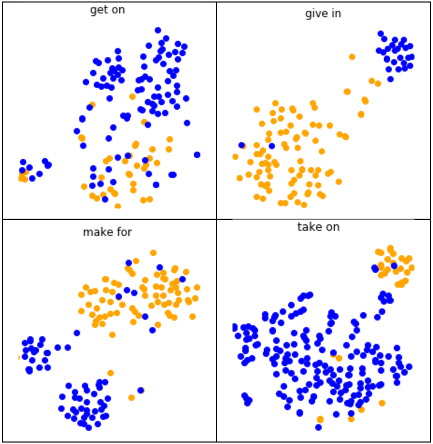


# Verb-Particle Classification

## Analysis



# Noun Compound Literality
## Task Definition

Non-Literal Literal

The crash course in litigation made me a better lawyer

# Noun Compound Literality

## Results

Non-Literal Literal

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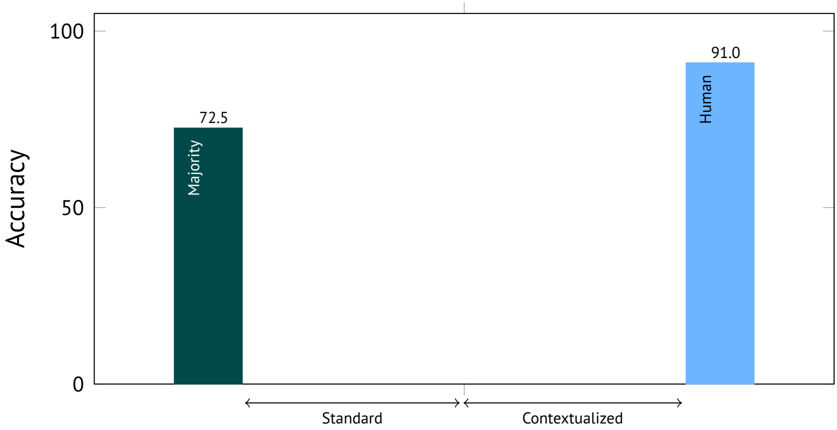

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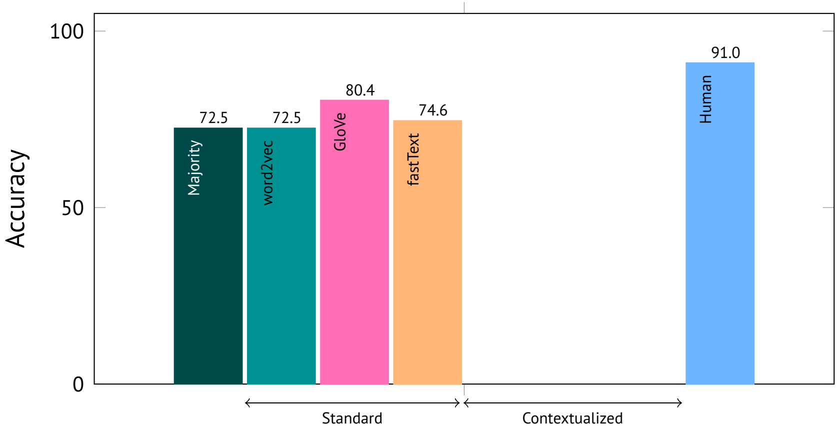

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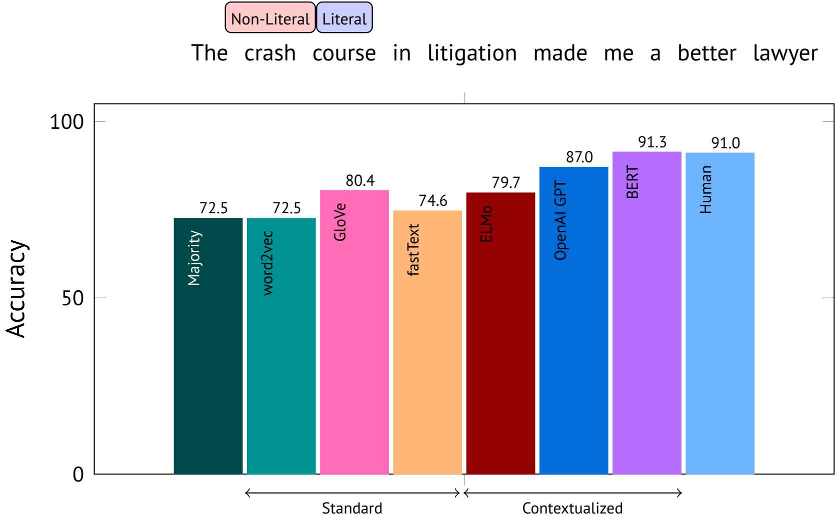

# Noun Compound Literality

## Detecting meaning shift → modeling meaning?

| **ELMo** | **OpenAI GPT** | **BERT** |
|---|---|---|
| The Queen and her husband were on a train **trip** from Sydney to Orange. | | |
| ride | to | travelling |
| carriage | headed | running |
| journey | heading | journey |
| heading | that | going |
| carrying | and | headed |

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| | | |
|---|---|---|
| Creating a guilt **trip** in another person may be considered to be psychological manipulation... | | |
| tolerance | that | reaction |
| fest | so | feeling |
| avoidance | trip | attachment |
| onus | he | sensation |
| association | she | note |

# Noun Compound Literality

## Non Decomposable Compounds

| ELMo | OpenAI GPT | BERT |
|---|---|---|
| ...I believe you are a snake **oil** salesman, a narcissist... | | |
| auto | in | oil |
| egg | and | pit |
| hunter | that | bite |
| rogue | charmer | jar |

Substitutes for the entire phrase.

# Implicit Meaning Tasks

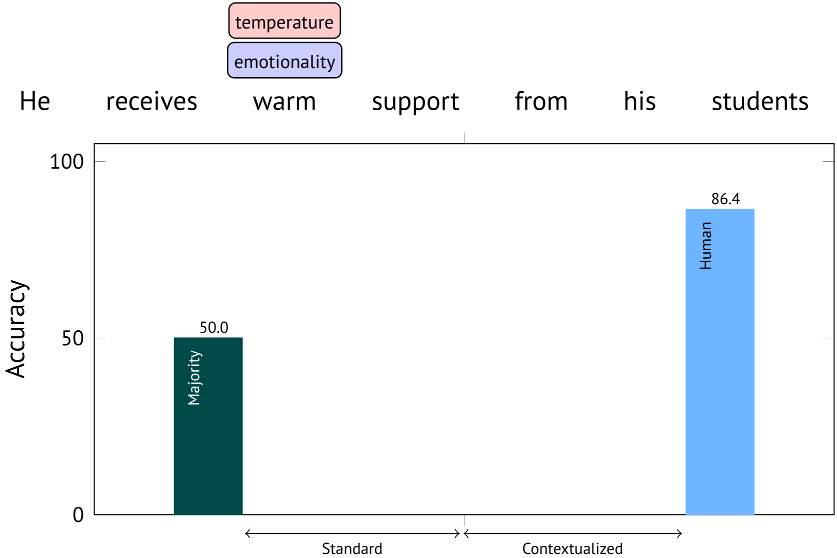
# Adjective-Noun Attributes
## Task Definition

temperature

emotionality

He receives warm support from his students

# Adjective-Noun Attributes
## Results



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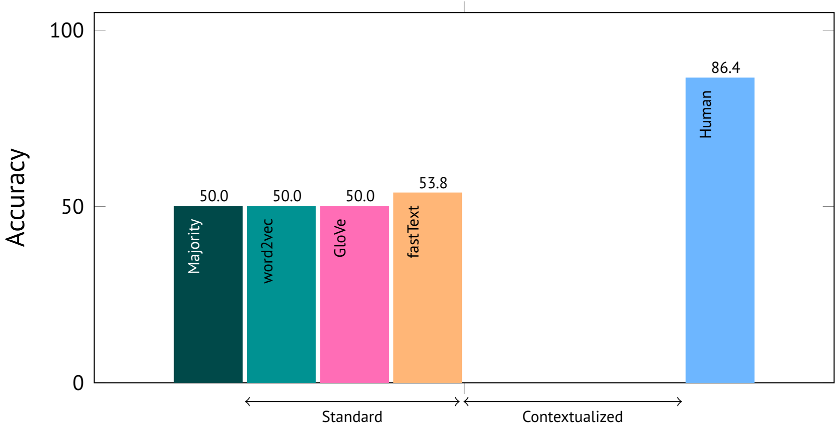

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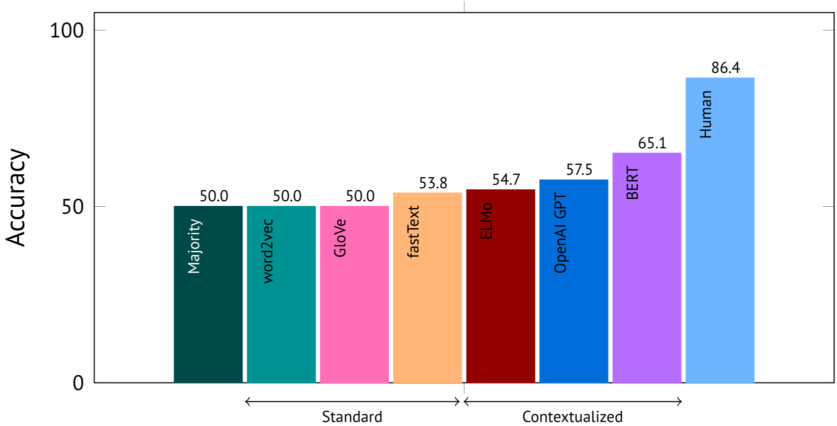


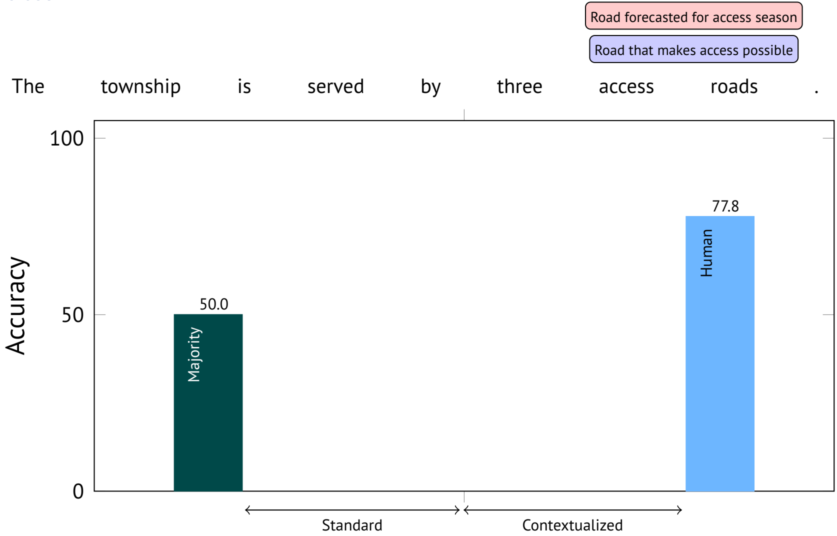
# Noun Compound Relations
## Task Definition

Road forecasted for access season

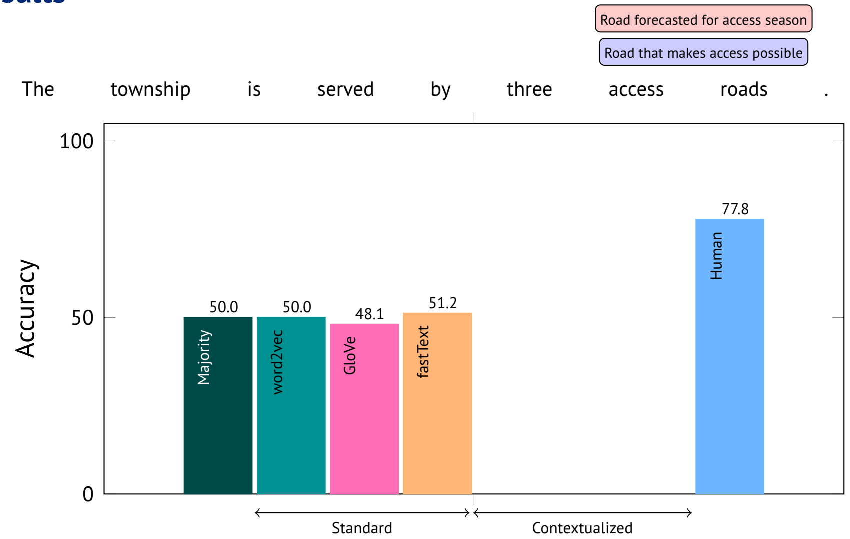
Road that makes access possible

The township is served by three access roads .

# Noun Compound Relations
## Results



# Noun Compound Relations
## Results



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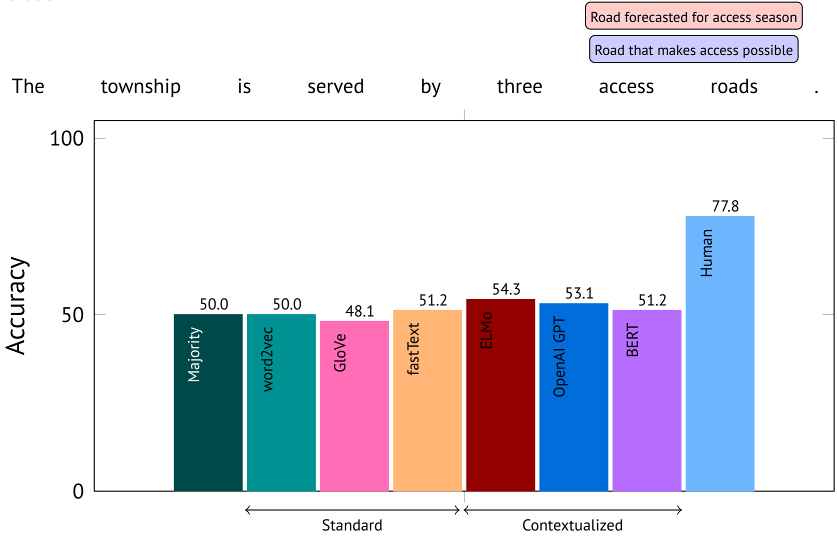

# Still a pain in the neck
## Recap

- Detecting meaning shift is a *piece of cake*

# Still a pain in the neck
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# Still a pain in the neck

## Recap

- Detecting meaning shift is a *piece of cake*

  for contextualized word embeddings

- Modeling the shifted, rare sense is not a *walk in the park*

- Modeling implicit information is a real *pain in the neck*

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- Context matters: trivially for meaning shift but also for revealing implicit meaning

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## Recap

- Context matters: trivially for meaning shift but also for revealing implicit meaning
  - **Noun Compounds** [Netzer and Elhadad, 1998]: context can override frequent interpretations ("*the market bench*").
  - **Adjective Noun Compositions** [Pavlick and Callison-Burch, 2016]: depending on the context some adjectives are trivially inferred ("*little baby*") or contradicting ("*Bush travelled to Michigan to talk about the Japanese economy*").

1. How well do contextualized embeddings represent phrases?
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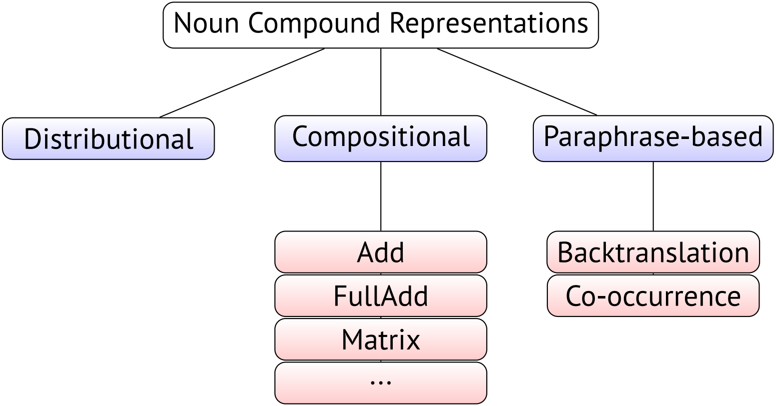
**A Systematic Comparison of English Noun Compound Representations.** Vered Shwartz. MWE-WN 2019

# Approaches


Noun Compound Representations
Distributional
Compositional
Paraphrase-based
Add
FullAdd
Matrix
...
Backtranslation
Co-occurrence

# Compositional Representations

$$\mathbf{f}\,\Big(\ \vec{v}_{w_1}\ ,\ \vec{v}_{w_2}\ ,\ \ldots\ ,\ \vec{v}_{w_k}\ \Big)$$

- $f(w_1\ w_2) = \alpha \cdot v_{w_1} + \beta \cdot v_{w_2}$ [Mitchell and Lapata, 2010]
- $f(w_1\ w_2) = Av_{w_1} + Bv_{w_2}$ [Zanzotto et al., 2010, Dinu et al., 2013]
- $f(w_1\ w_2) = tanh(W \cdot [v_{w_1}; v_{w_2}])$ [Socher et al., 2012]
- ...

# Compositional Representations

**f (** $\vec{v}_{w_1}$ **,** $\vec{v}_{w_2}$ **, … ,** $\vec{v}_{w_k}$ **)**

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- ...

**Generalization at the constituent level, e.g.:**

*syndicate representative*
f(worker, representative)
f(player, representative)
f(crack, dealer)
f(company, spokesman)
f(industry, commissioner)

# Paraphrase-based Representations

$f(w_1 w_2) \approx f(paraphrase)$

- **Backtranslation**: [Wieting et al., 2015]
  *baby oil* $\rightarrow$ *huile pour bébé* $\rightarrow$ *oil for baby*
- **Co-occurrence** of the constituents, e.g. *cake made of apples*
- ...

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**Generalization at the constituent level, e.g.:**

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f(worker, representative)
f(union, representative)
f(group, manager)
f(employee, representative)
f(student, representative)

# What is the best representation?
## [Dima, 2016]

- **FullAdd** ($Av_{w_1} + Bv_{w_2}$) vs. **Matrix** ($tanh(W \cdot [v_{w_1}; v_{w_2}])$)

# What is the best representation?
## [Dima, 2016]

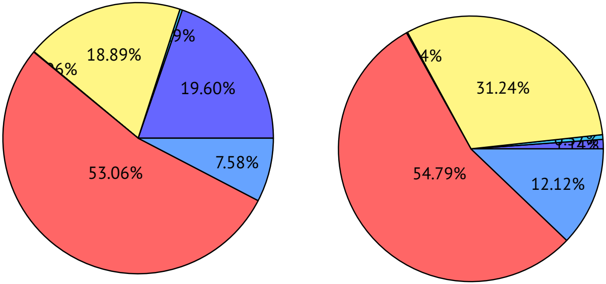
- **FullAdd** ($Av_{w_1} + Bv_{w_2}$) vs. **Matrix** ($tanh(W \cdot [v_{w_1}; v_{w_2}])$)
- Good performance is achieved even with $f(w_1, w_2) = [w_1; w_2]$
- No substantial gain from compositional representations due to lexical memorization

# Our work

| | |
|---|---|
| **Nearest Neighbours** | types of neighbours for rare/frequent compounds |
| **Attribute Prediction** | is *cheese wheel* round? |
| **Relation Classification** | what is the relationship in *baby oil*? |

# Main Takeouts
## No superior representation

- Many neighbours are either incorrect or trivial:




**Matrix** (rare) **Backtranslation** (rare)

- Rare words
- Share constituents with the target compound
- Other noun compounds
- Other words

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- **Attributes**: paraphrase-based
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- **Relations**: compositional + small window
  but with bad absolute performance in strict evaluation setups
- [Dima et al., 2019]: more composition functions!

1. How well do contextualized embeddings represent phrases?
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**Olive Oil Is Made of Olives, Baby Oil Is Made for Babies: Interpreting Noun Compounds Using Paraphrases in a Neural Model.** Vered Shwartz and Chris Waterson. NAACL 2018

**Paraphrase to Explicate: Revealing Implicit Noun-Compound Relations.** Vered Shwartz and Ido Dagan. ACL 2018

# Noun Compounds

- Express implicit relationship between the constituent nouns:

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- They are like “text compression devices” [Nakov, 2013]

# Noun Compounds

- Express implicit relationship between the constituent nouns:
  - *apple cake*: cake *made of* apples
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- They are like “text compression devices” [Nakov, 2013]
- We’re pretty good at decompressing them!

# Noun-Compound Interpretation Tasks

**Bracketing**
*[[pumpkin spice] latte]*

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*[[pumpkin spice] latte]*

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*apple cake* $\rightarrow$ ingredient
*birthday cake* $\rightarrow$ time

# Noun-Compound Interpretation Tasks

**Bracketing**
*[[pumpkin spice] latte]*

**Compositionality Prediction**
is *spelling bee* related to *bee*?

**Relation Classification**
*apple cake* → ingredient
*birthday cake* → time

**Paraphrasing**
*cake* made of *apples*
*cake* eaten on a *birthday*

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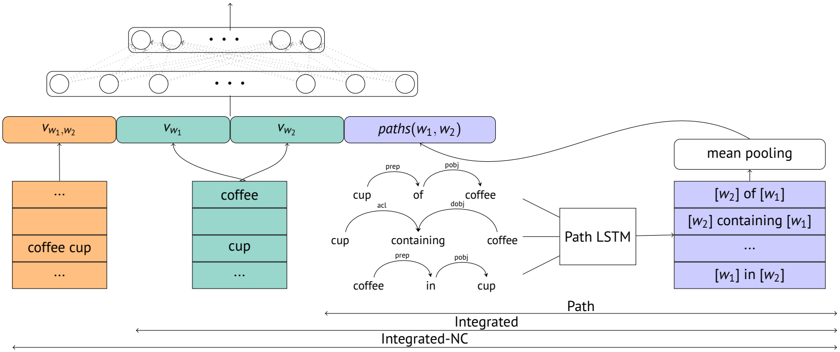
  - Split the dataset lexically

# Overall Architecture



# Evaluation - Datasets

- Dataset: [Tratz, 2011]

| | | |
|---|---|---|
| **Purpose/Activity Group** | | |
| PERFORM&ENGAGE_IN | 11.5% | cooking pot |
| CREATE-PROVIDE-GENERATE-SELL | 4.8% | nicotine patch |
| OBTAIN&ACCESS&SEEK | 0.9% | shrimp boat |
| MITIGATE&OPPOSE | 0.8% | flak jacket |
| ORGANIZE&SUPERVISE&AUTHORITY | 1.6% | ethics authority |
| PURPOSE | 1.9% | chicken spit |
| **Ownership, Experience, Employment, Use** | | |
| OWNER-USER | 2.1% | family estate |
| EXPERIENCER-OF-EXPERIENCE | 0.5% | family greed |
| EMPLOYER | 2.3% | team doctor |
| USER_RECIPIENT | 1.0% | voter pamphlet |
| **Temporal Group** | | |
| TIME-OF1 | 2.2% | night work |
| TIME-OF2 | 0.5% | birth date |
| **Location and Whole+Part/Member of** | | |
| LOCATION | 5.2% | hillside home |
| WHOLE+PART_OR_MEMBER_OF | 1.7% | robot arm |

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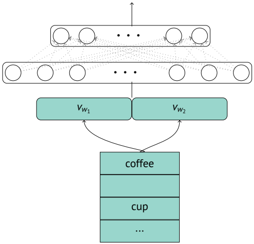
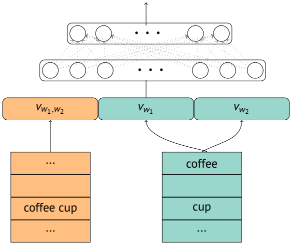
- Datatset splits:
  - Random 75:20:5 (like previous work)
  - Lexical-full [Levy et al., 2015]
  - Lexical-head
  - Lexical-mod

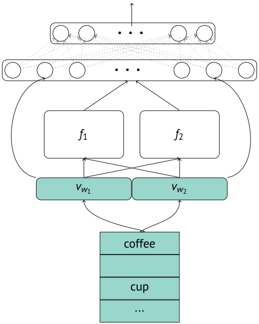
# Evaluation - Baselines




Dist




Dist-NC




Compositional [Dima, 2016]

# Evaluation - Results

| Dataset | Split | Best Baseline | Path | Int | Int-NC |
|---|---|---|---|---|---|
| Tratz-fine | Rand | **0.725** | 0.538 | 0.714 | 0.692 |
| | $Lex_{head}$ | 0.458 | 0.448 | **0.510** | 0.478 |
| | $Lex_{mod}$ | 0.607 | 0.472 | **0.613** | 0.600 |
| | $Lex_{full}$ | 0.363 | 0.423 | 0.421 | **0.429** |
| Tratz-coarse | Rand | **0.775** | 0.586 | 0.736 | 0.712 |
| | $Lex_{head}$ | 0.538 | 0.518 | **0.569** | 0.548 |
| | $Lex_{mod}$ | 0.645 | 0.548 | **0.646** | 0.632 |
| | $Lex_{full}$ | 0.409 | 0.472 | **0.475** | 0.478 |

- Random split: distributional/compositional baselines outperform all other methods, by memorizing words.

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- Lexical split: our methods perform better.

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- The performance gap is larger in lexical-full.

# Analysis

## Which relations can the path-based model learn?

| relation | path | examples |
|---|---|---|
| measure | [$w_2$] varies by [$w_1$] | *state limit* |
| | 2,560 [$w_1$] portion of [$w_2$] | *acre estate* |
| personal title | [$w_2$] Anderson [$w_1$]/title | *Mrs. Brown* |
| | [$w_2$] Sheridan [$w_1$]/title | *Gen. Johnson* |
| create-provide-generate-sell | [$w_2$] produce [$w_1$] | *food producer* |
| | [$w_2$] manufacture [$w_1$] | *engine plant* |
| time-of1 | [$w_2$] begin [$w_1$] | *morning program* |
| | [$w_2$] held Saturday [$w_1$] | *afternoon meeting* |
| substance-material - ingredient | [$w_2$] made of wood and [$w_1$] | *marble table* |
| | [$w_2$] material includes type of [$w_1$] | *steel pipe* |

# Analysis

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- lexicalized has no indicative paths! (e.g. *soap opera*)

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- lexicalized has no indicative paths! (e.g. *soap opera*)
- partial_attribute_transfer (e.g. *bullet train*) has few indicative paths (e.g. "*train as fast as a bullet*")

# Noun Compound Relation Classification

## Recap

- Joint corpus occurrences improve the performance in strict evaluation setups $\vee$

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# Noun Compound Relation Classification
## Recap

- Joint corpus occurrences improve the performance in strict evaluation setups V
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- Lexical splits help prevent lexical memorization V
- The dataset is noisy, it's difficult to label each NC to a single relationship ×

# Noun-Compound Interpretation Tasks

**Bracketing**
*[[pumpkin spice] latte]*

**Compositionality Prediction**
is *spelling bee* related to *bee*?

**Relation Classification**
*apple cake* → ingredient
*birthday cake* → time

**Paraphrasing**
*cake* made of *apples*
*cake* eaten on a *birthday*

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    - Even when we see them for the first time

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# Generalizing Existing Knowledge

- What can cake be made of?

Corpus of Contemporary American English

SEARCH | FREQUENCY | CONTEXT | HELP

SEE CONTEXT: CLICK ON WORD OR SELECT WORDS + [CONTEXT] [HELP...]    COMPARE

| | | CONTEXT ALL FORMS (SAMPLE): 100 200 500 | FREQ | TOTAL 237 \| UNIQUE 119 + |
|---|---|---|---|---|
| 1 | | CAKE WITH CHOCOLATE | 31 | |
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| 3 | | CAKE WITH STRAWBERRIES | 10 | |
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| 5 | | CAKE WITH CARAMEL | 7 | |
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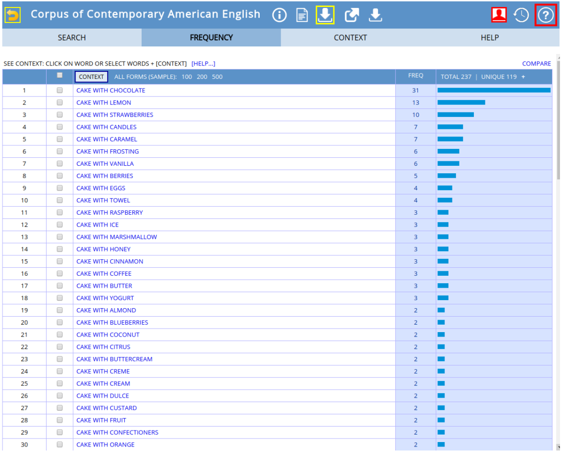

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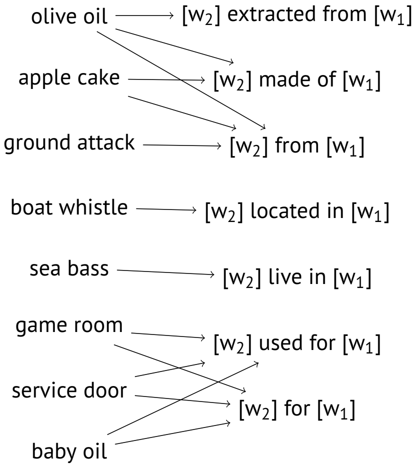
- Parsley (sort of) fits into this distribution
- Similar to “selectional preferences” [Pantel et al., 2007]

# Noun-Compound Paraphrasing

# Motivation

Given a noun-compound $w_1 w_2$, express the relation between the head $w_2$ and the modifier $w_1$ with multiple prepositional and verbal paraphrases [Nakov and Hearst, 2006]



# Evaluation Setting

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- Evaluated for correlation with human judgments
  - Gold paraphrase score: how many annotators suggested it?

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- Prior work provides partial solutions to either (1) or (2)

# Model

# Multi-task Reformulation

- Training example {$w_1$ = apple, $w_2$ = cake, $p$ = "[$w_2$] made of [$w_1$]"}

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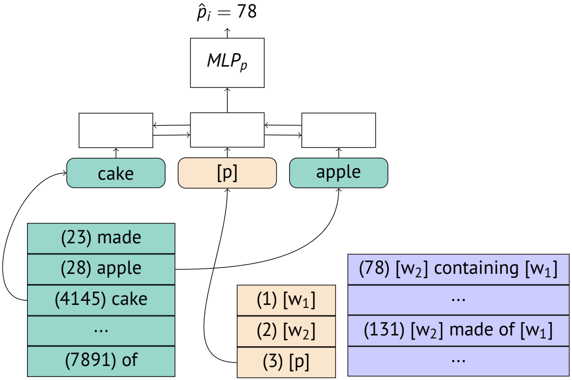
# Main Task (1): Predicting Paraphrases

## What is the relation between *apple* and *cake*?

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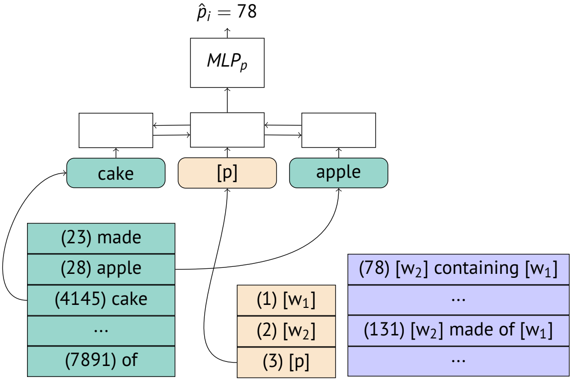


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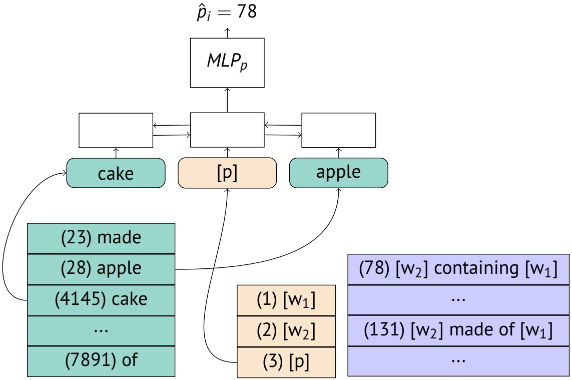


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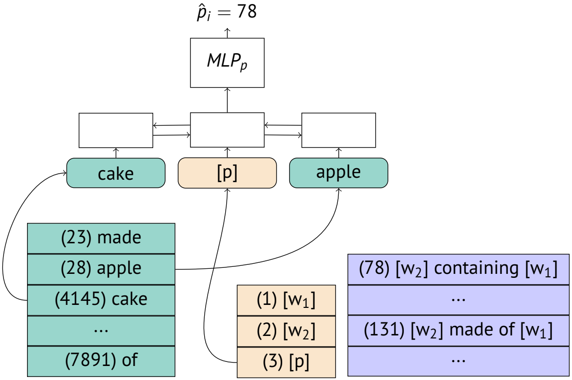


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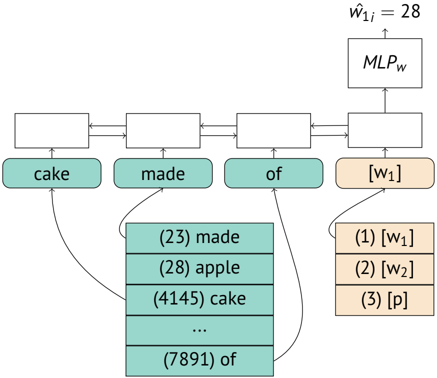
- (1) Generalizes NCs: *pear tart* expected to yield similar results

# Helper Task (2): Predicting Missing Constituents

## What can *cake* be made of?

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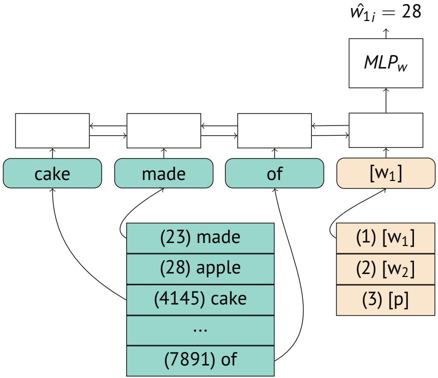


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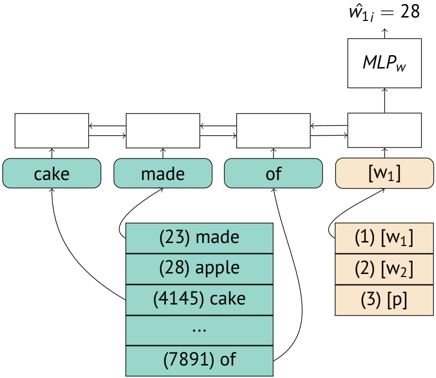


- Encode placeholder in "cake made of [$w_1$]" using biLSTM
- Predict an index in the word vocabulary
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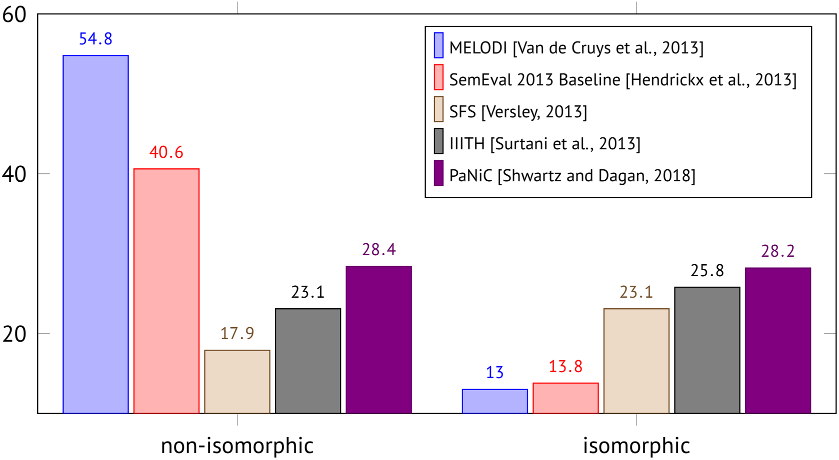
- Learn to re-rank the paraphrases
  - to better correlate with human judgments
- SVM pair-wise ranking with the following features:
  - POS tags in the paraphrase
  - Prepositions in the paraphrase
  - Length
  - Special symbols
  - Similarity to predicted paraphrase

# Results



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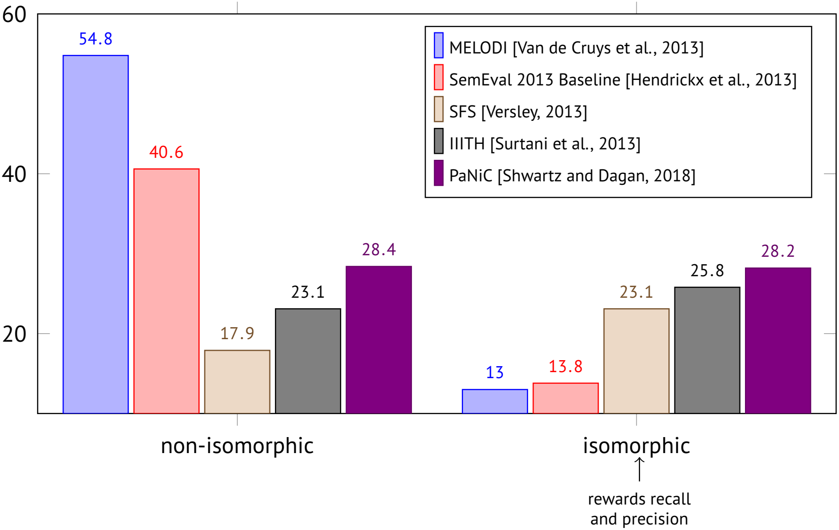
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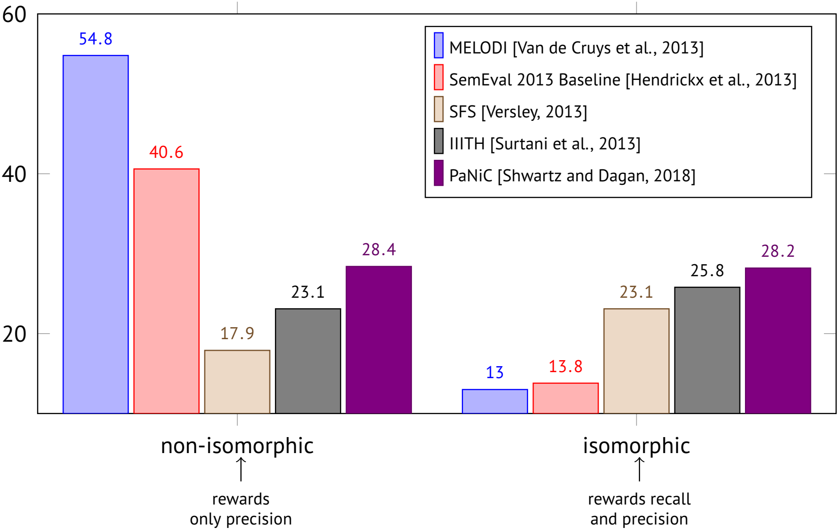

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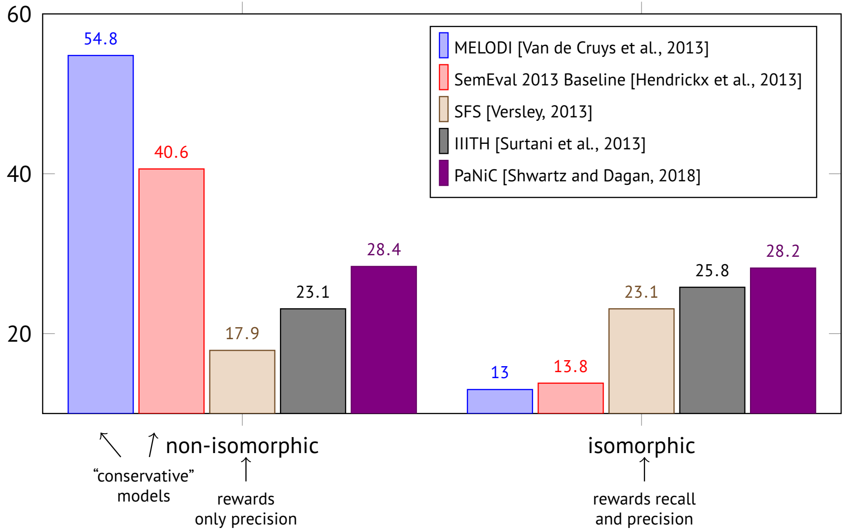

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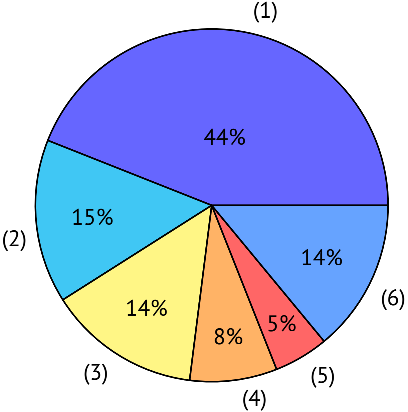
# Error Analysis

## False Positive

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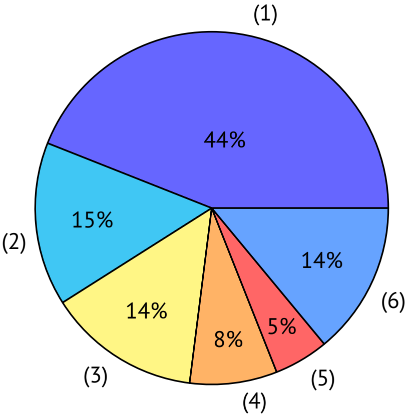


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2. Too specific
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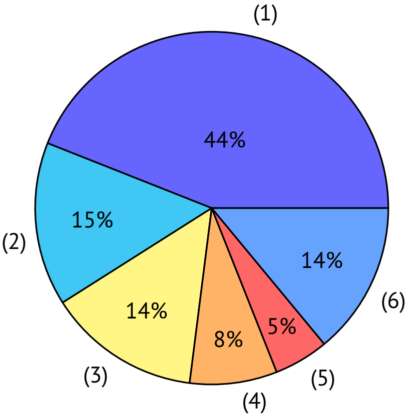


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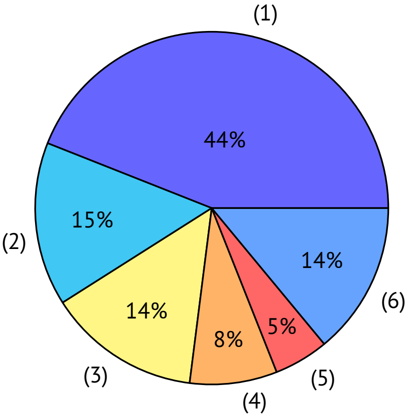
   (“life *of women in* community”)
3. Incorrect prepositions

# Error Analysis
## False Positive




1. Valid, missing from gold-standard
   (“discussion by group”)
2. Too specific
   (“life *of women in* community”)
3. Incorrect prepositions
   E.g., n-grams don’t respect syntactic structure: “rinse away the oil from baby ’s head” $\Rightarrow$ “oil from baby”

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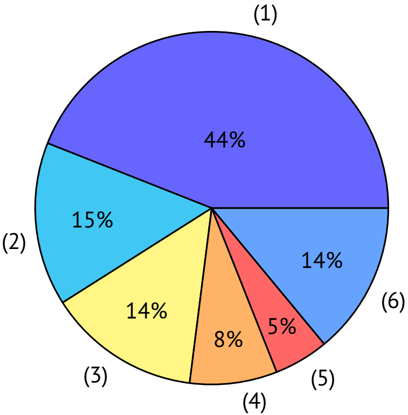


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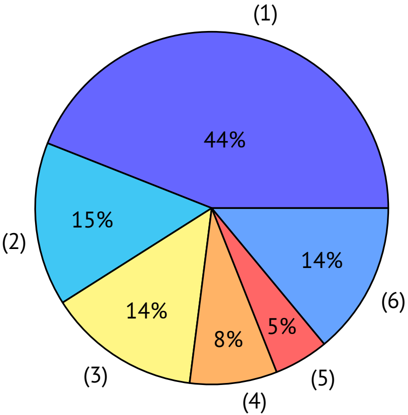


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5. Borderline grammatical
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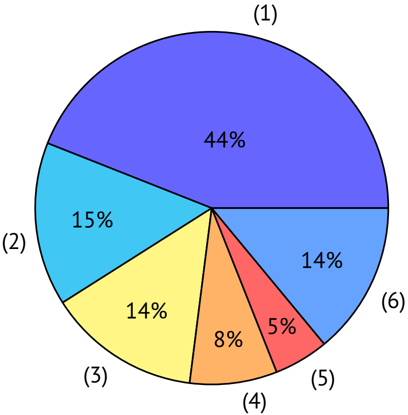


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6. Other errors

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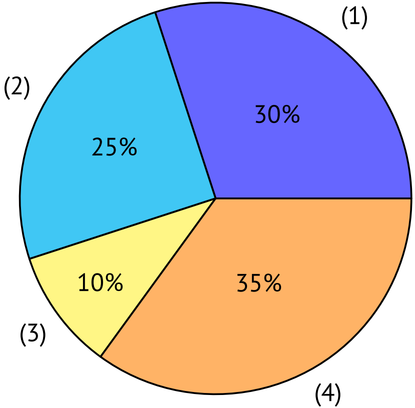
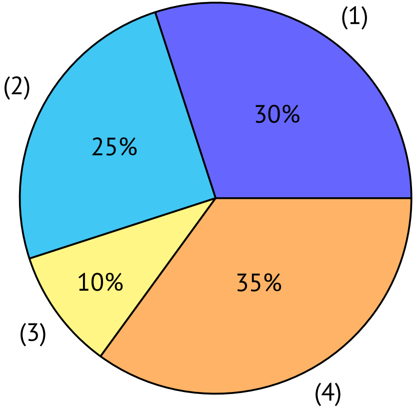



1. Long paraphrase ($n > 5$)

# Error Analysis

## False Negative




1. Long paraphrase ($n > 5$)
2. Determiners
   ("mutation of **a** gene")

# Error Analysis

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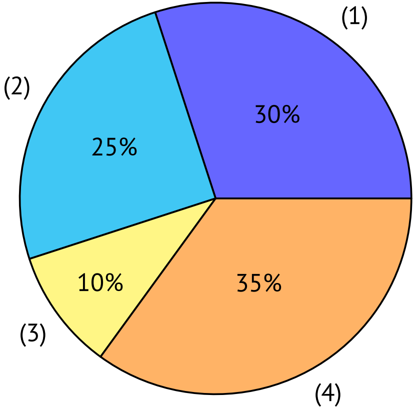


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2. Determiners ("mutation of **a** gene")
3. Inflected constituents ("holding of share**s**")

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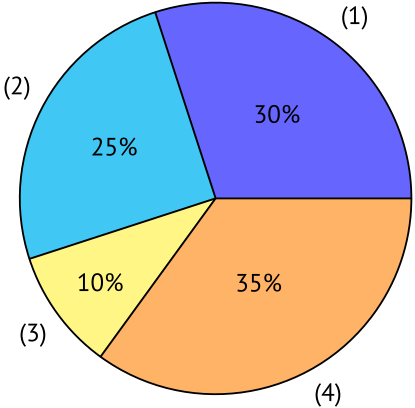


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# Noun Compound Paraphrasing
## Recap

- A model for generating paraphrases for given noun-compounds

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- A model for generating paraphrases for given noun-compounds
- Better generalization abilities:
  - Generalize for unseen noun-compounds
  - Embed semantically-similar paraphrases in proximity
- Improved performance in challenging evaluation settings

# Future Directions
## in phrase representations

# Can we learn phrase meanings like humans do?

- [Cooper, 1999]: how do L2 learners process idioms?
  - **Infer from context:** 28% (57% success rate)
  - **Rely on literal meaning:** 19% (22% success rate)
  - ...

# Inferring from context

**Furious Meghan Markle says she won’t fall for dad’s ‘crocodile tears’ after he claimed ‘she’d be better off if he were dead’**

FURIOUS Meghan Markle has said she won't fall for her dad's "crocodile tears" after he claimed "she'd be better off if he were dead".

The Duchess of Sussex reportedly told pals Thomas Markle is using "emotional blackmail" to try and manipulate her but she's had "enough already".

## We need “extended” contexts

[Asl, 2013]: more successful idiom interpretation with extended contexts (stories)

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## We need “extended” contexts

[Asl, 2013]: more successful idiom interpretation with extended contexts (stories)

## We need richer context modeling

- Characters in the story
- Relationships between them
- Dialogues
- …

# Relying on literal meaning

*"Robert knew he was robbing the cradle by dating a sixteen-year-old girl"*

**We need world knowledge**

*"Cradle is something you put the baby in"*

# Relying on literal meaning

*"Robert knew he was robbing the cradle by dating a sixteen-year-old girl"*

**We need world knowledge**
*"Cradle is something you put the baby in"*

**We need to be able to reason**
*"You're stealing a child from a mother"*

*"So **robbing the cradle** is like dating a really young person"*

[Cooper, 1999]

# Thank you!
# Questions?

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