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# Distributional Identification of Non-Referential Pronouns

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# Non-Referential Pronouns

- No antecedent, e.g. “**It**’s raining men”
- Input: context of pronoun:  
\_ ’s raining men
- Output:  
Non-referential?  
Yes/No



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# Outline

1. Pronoun Resolution and Non-Referential Pronouns
2. Distributional Identification
3. Methodology
4. Experiments
5. Results

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# 1) Pronoun Resolution

- Pronouns like *he, she, his, they, them* are used in place of nouns in text:
  - “*It* was founded in 1940 by Dick and Mac McDonald in San Bernardino, California”
- Resolve pronoun *It* to antecedent (McDonald’s)
  - For QA, Summarization, Translation, etc.

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# Non-Referential Pronouns

- Not all pronouns refer to preceding noun
- The pronoun *it* can refer to whole clauses or sentences, or simply be a grammatical placeholder (pleonastic):

“*It* is important to eat your veggies.”

“*It* is raining cats and dogs... and men.”

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# Prevalence

- *it* accounts for about 1% of tokens in text
- Between 25% and 50% of these are non-referential
- Non-referential pronouns are not just an English phenomenon:
  - “Wie geht **es** Ihnen?”
  - “S’il vous plaît.”
  - Same in pro-drop languages

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# Previous Work

- **Hirst (1981)**: detect non-referentials, “lest precious hours be lost in bootless searches for textual referents.”
- **Recent work**: rule-based or machine learned systems based on manually-defined features of the pronoun’s context

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## 2) Distributional Identification

- Our hypothesis:
  - The contexts of non-referential pronouns are unique to these pronouns
  - Therefore in text these contexts mostly occur with the pronoun *it*
- If we can estimate how often a context occurs with *it*, we can estimate how likely it is to be non-referential.



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# Distributional Identification

- E.g.
  - “You can make *it* in advance.”
  - “You can make *it* in Hollywood.”
- How often do the contexts have fillers other than *it*?

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# Distributional Identification

- Convert to a pattern:  
“make \_ in advance”
- Collect counts from N-gram data:
  - “make *it/them* in advance”
    - 442 vs. 449 occurrences in N-gram data
  - “make *it/them* in Hollywood”
    - 3421 vs. 0 occurrences in N-gram data

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# Distributional Identification

- Convert to a pattern:

“make \_ in advance”

- Collect counts from N-gram data

Referential

– “make *it*/*them* in advance”

- 442 vs. 449 occurrences in N-gram data

– “make *it*/*them* in Hollywood”

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# Distributional Identification

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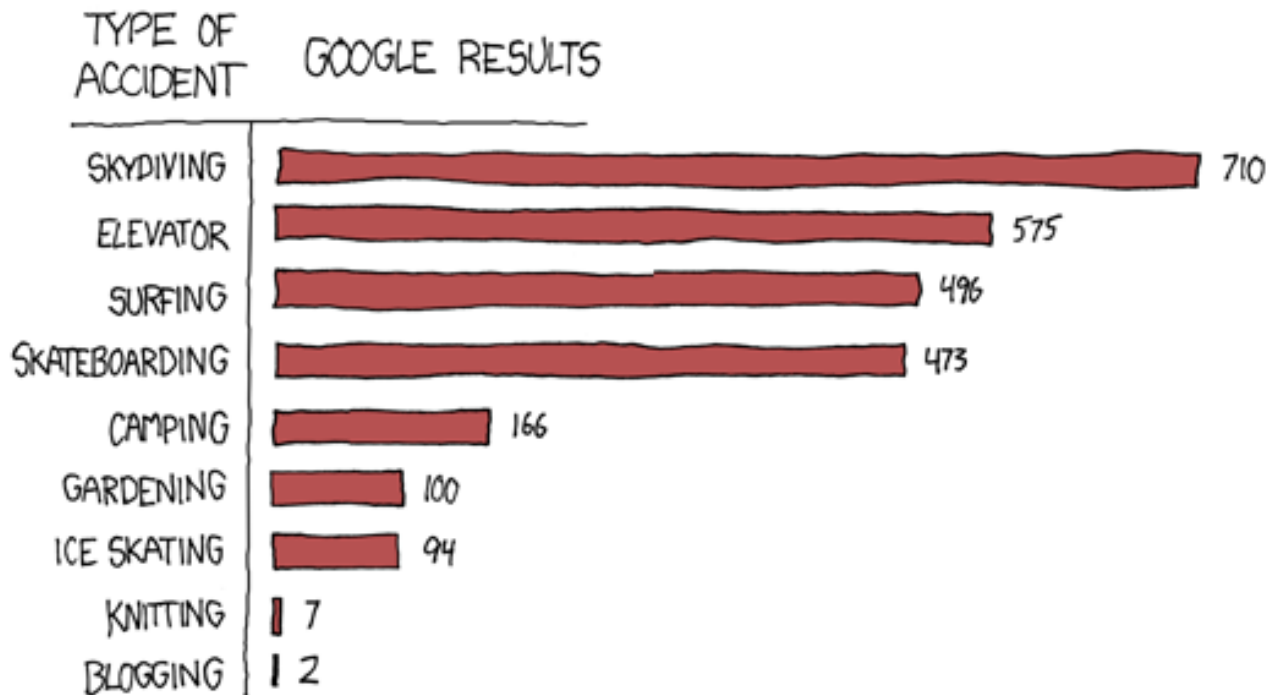
- 3421 vs. 0 occurrences in N-gram data

Referential

Non-Referential

# DANGERS

INDEXED BY THE NUMBER OF GOOGLE RESULTS FOR  
"DIED IN A \_\_\_\_\_ ACCIDENT"



From:  
xkcd.com

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# 3) Methodology

- How much context to include in a pattern?
- There are many possible patterns that span the pronoun – which do we use?
- How do we use the distribution for classification?

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# Methodology

- How much context?
  - N-gram corpus has up to 5-grams

- E.g.

... said here Thursday that *it* is unnecessary to continue ...

said here Thursday that \_

here Thursday that \_ is

Thursday that \_ is unnecessary

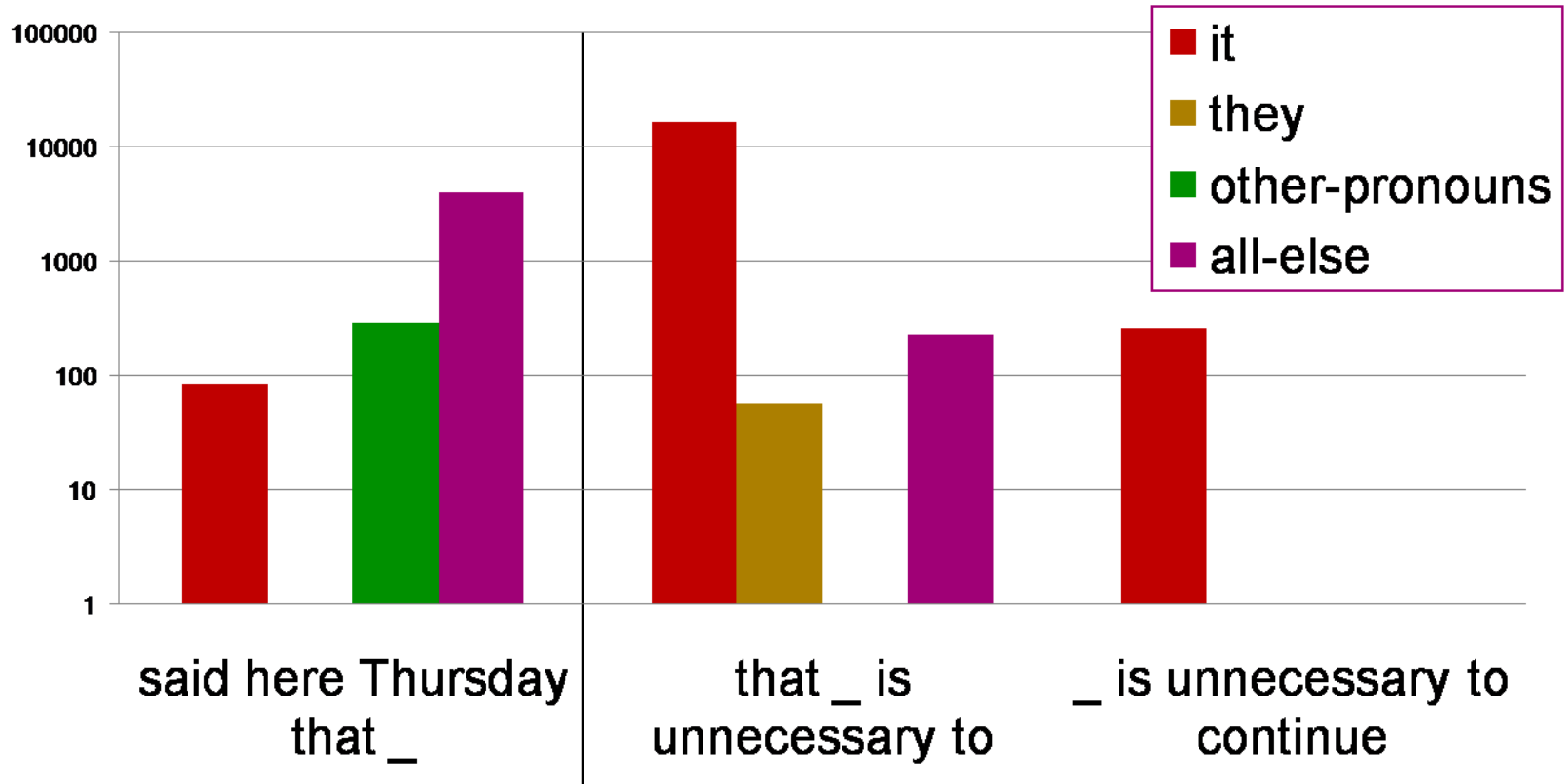
that \_ is unnecessary to

\_ is unnecessary to continue

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# Filler Counts by Type/Position





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# Combining Counts

- Use supervised machine learning to optimally combine count information
- Define non-referential as positive class, referential as negative
- Use *MaxEnt* to learn classifier
- Features:  **$\log(\#counts)$** 
  - indexed by pattern position and filler type

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# Labelled Data

- Data indicates, for every instance of *it*, whether it refers to preceding noun or not
- Extracted this information directly from MUC-7 coreference corpus
- Also annotated data from other sources
  - Good agreement among three annotators (K between 0.8 and 0.9)

# Labelled Data

Data Set	Number of <i>It</i>	% Non-Referential
Europarl	279	50.9
Science News	1020	32.6
WSJ	709	25.1
MUC	129	31.8
Train	1069	33.2
Test	1067	31.7

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# 4) Experiments

- Evaluation Criteria:
  - Precision:

Percent of our system's positive non-referential decisions which are truly non-referential
  - Recall:

Percent of true non-referentials that our system labels as positive

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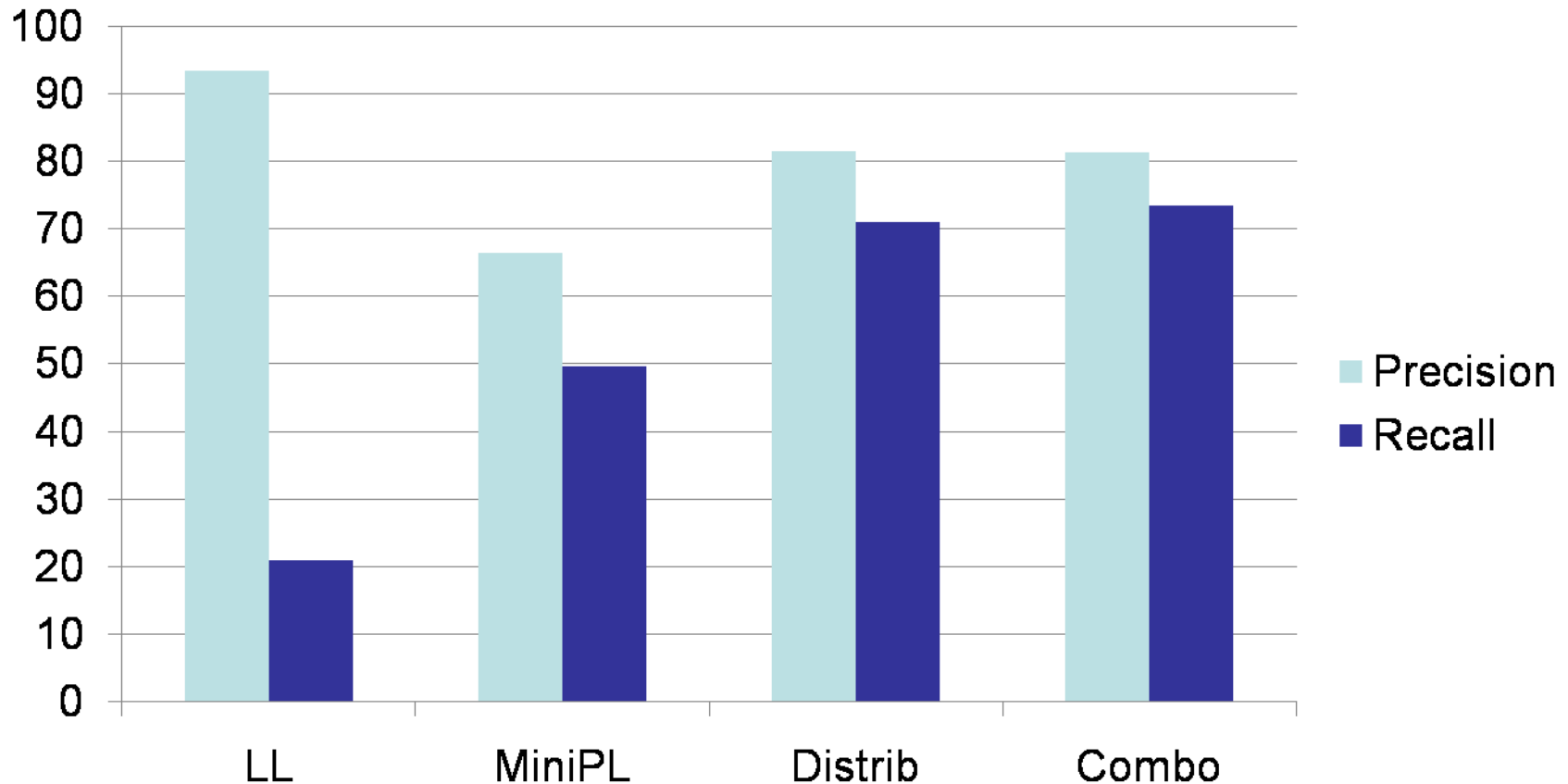
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# Experiments

- Comparison Approaches:

<b>LL</b>	Lappin & Leass's syntactic, rule-based non-referential pronoun detector
<b>MiniPL</b>	Extended version of LL
<b>Distrib</b>	Our distributional approach
<b>Combo</b>	Distrib + extra features for LL and MiniPL decisions

# Train/Test Performance (%)



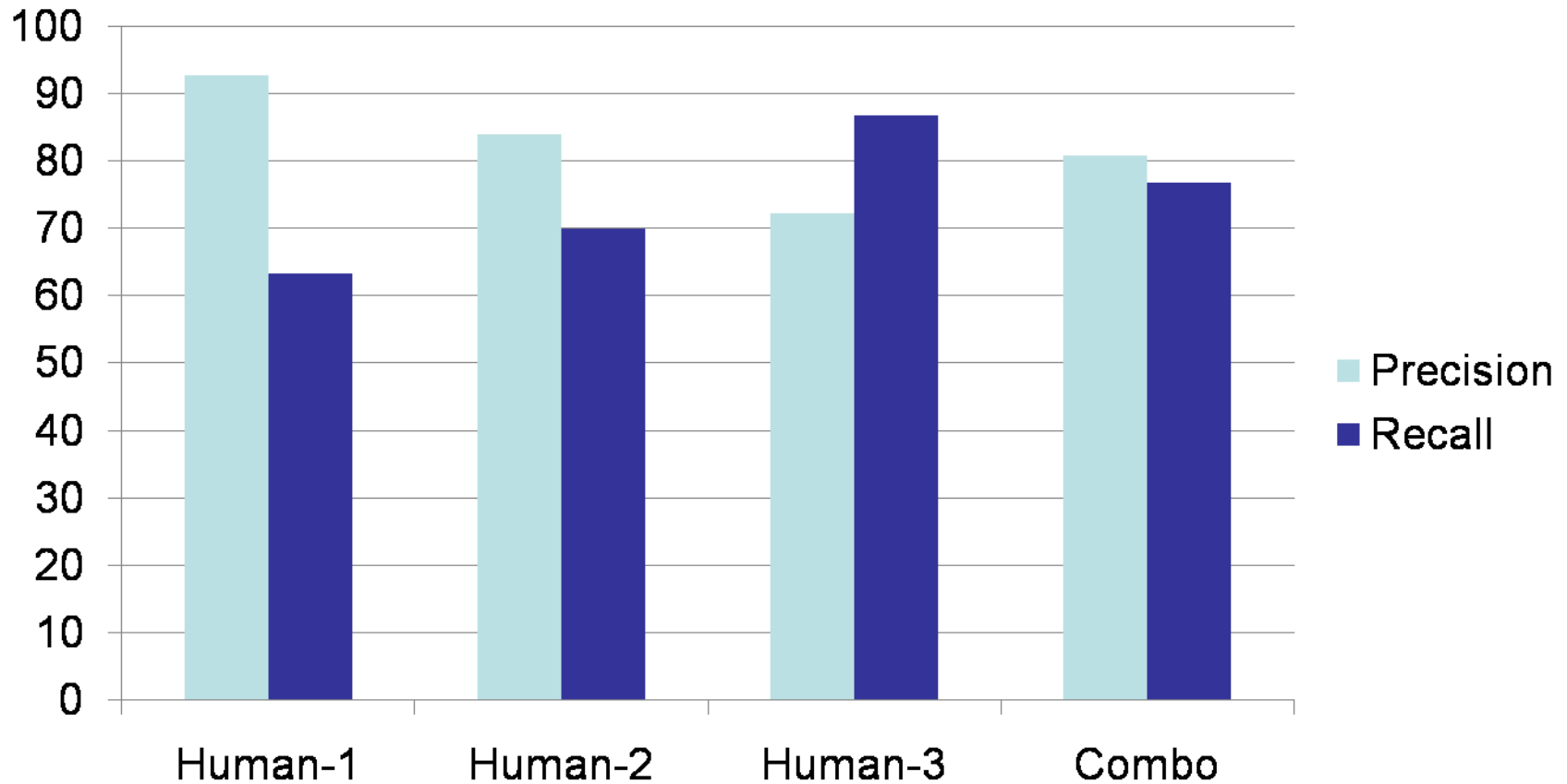
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# Analysis

- To our knowledge, best results on this task
- Decision ultimately based only on 9-token context window around pronoun
  - no other info from previous discourse
- Question: How well can humans do with the same information?

# Human Performance





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# Error Analysis

- “*It* takes an astounding amount ...

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# Error Analysis

- “*It* takes an astounding amount ... of time to compare very long DNA sequences with each other.”

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# Error Analysis

- “*It* takes an astounding amount ... of time to compare very long DNA sequences with each other.”
- “... the machine he had installed *it* on.”

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# Error Analysis

- “*It* takes an astounding amount ... of time to compare very long DNA sequences with each other.”
- “... the machine he had installed *it* on.”
  - Need information about preceding candidate nouns. Non-referential detection should ultimately be done jointly with pronoun resolution (cf. Denis and Baldrige (2007))

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# Conclusion

- Presented simple, distributional technique to classify non-referential pronouns
- Simple to implement, potentially portable to other languages
- State-of-the-art results
- Experimental data is available
- Lots more details and ideas in the paper



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# Additional Slides

1. Pro-drop languages
2. Combining Counts
3. N-gram Data

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# Pro-drop Languages

- Omitted pronouns (zero pronouns) are often non-referential:
  - “Es importante que nosotros...”  
(it is important that we...)
  - “¡Esta lloviendo [hombres]!”
- Need to know which zero pronouns are referential before resolving them:
  - “Es importante para mí.”



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# Combining Counts

- Intuitively, classifier should assign:
  - positive weights to the counts of *it* fillers
  - negative weights to the other counts
  - higher weights to counts from more predictive context positions

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# N-gram Data

- N-gram counts:
  - Google Web 1T 5-gram Corpus Version 1.1
  - Generated from roughly 1 trillion tokens of online text
  - Only includes tokens occurring more than 200 times, n-grams occurring more than 40 times