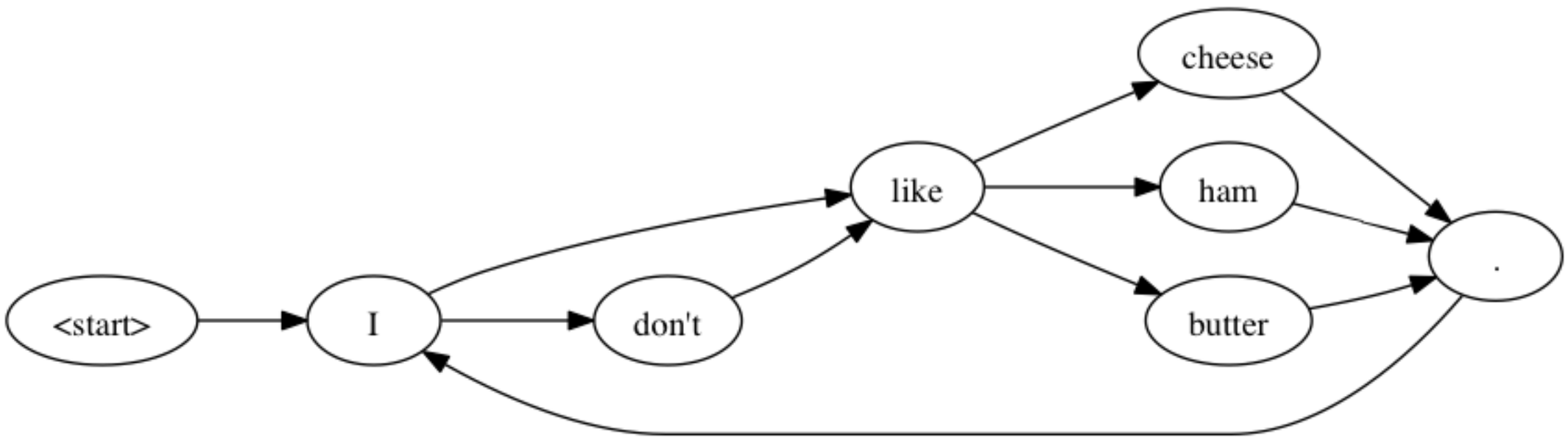
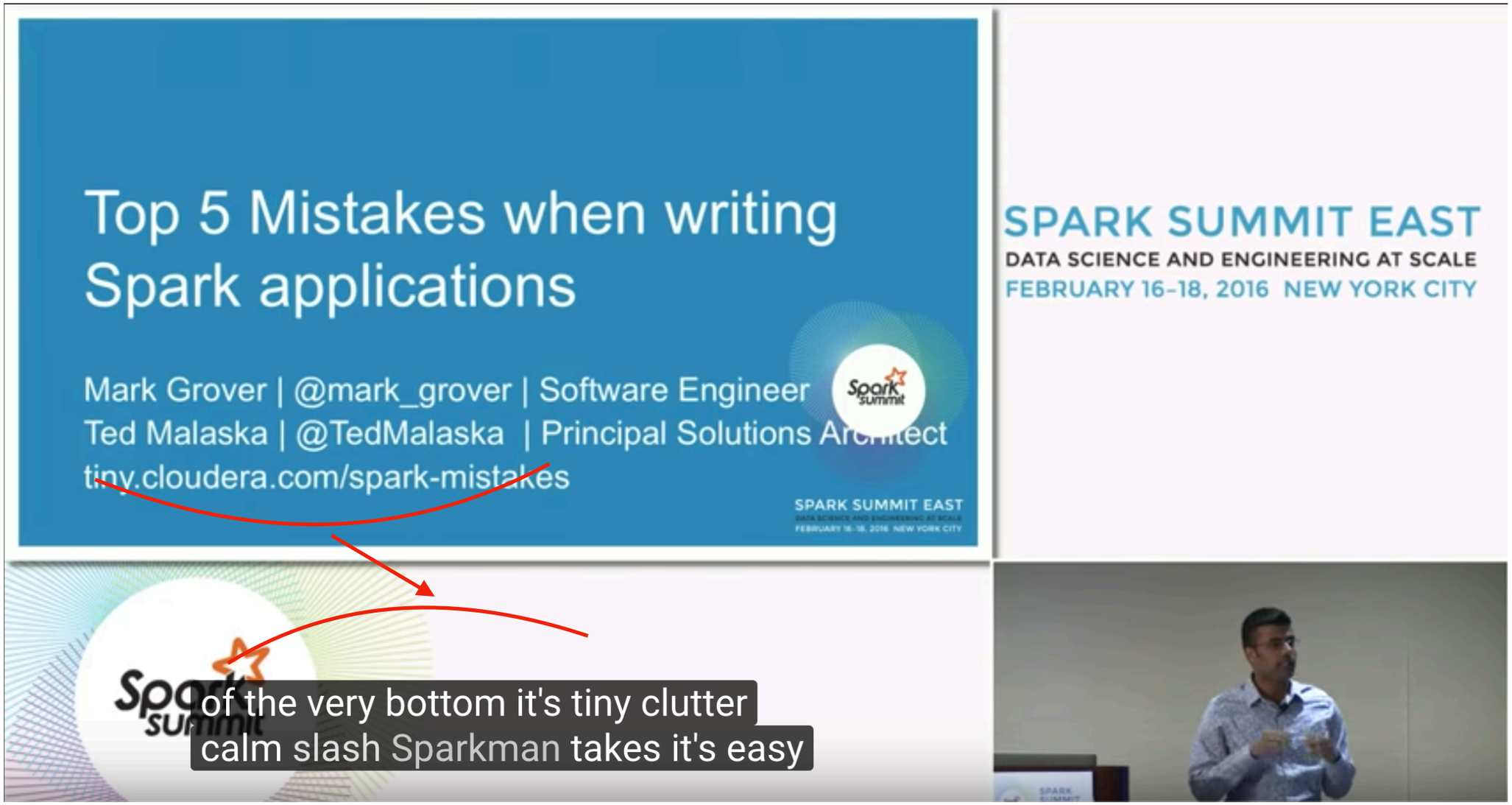
# Language models

Eugeny Malyutin



# Motivation:

There are a lot of tasks to estimate whether text is «natural» or «comprehensible».
Sometimes a clever way to estimate the word sequence probability is enough



# Possible tasks:

- **Machine translation:**
  他 向 记者 介绍了 主要 内容
  He to reporters introduced main content

  As part of the process we might have built the following set of potential rough English translations:
  he introduced reporters to the main contents of the statement
  he briefed to reporters the main contents of the statement
  he briefed reporters on the main contents of the statement

**What do you prefer?**

# Possible tasks:

- **Machine translation:**
  他 向 记者 介绍了 主要 内容
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  he introduced reporters to the main contents of the statement
  he briefed to reporters the main contents of the statement
  **he briefed reporters on the main contents of the statement**

# References:

- Dan Jufarsky https://web.stanford.edu/~jurafsky/slp3/
- P. Braslavsky's course. https://stepik.org/course/1233/ (yep, this is in Russian)

# Another tasks:

- **Speech recognition / machine translation / spelling correction / augmentative communication:**
  e.g.: having generated several possible decodings of the phrase, one has to choose ‘the most probable’ (from the language’s point of view)

- **Information retrieval:**
  ranking: for every document **d** we build ‘its language model’ and sort all documents by **P(q|d)** (where **q** is a query)

- **Text generation (spam also):**
  text generators, imitating the provided text collection’s style: Blabla-bots, spam, science articles, linux core C++ code ( **http://karpathy.github.io/2015/05/21/rnn-effectiveness/** )
  //this blogue post is not about language models but about fun.

# Intuition:

**Hello, how are … ?**

# Intuition:

**Hello, how are … ?**

on? are?

# Intuition:

**Hello, how are … ?**

you

**Language model** allows us to estimate the probability of any sequence of words (alternative formulation: to estimate the probability of the next word) // Why are these formulations equivalent?.

# Intuition:

Conditional probability:

$$P(Y|X) = \frac{P(X,Y)}{P(Y)} \Rightarrow P(X,Y) = P(Y|X)P(X)$$

Chain rule for greater number of variables:

$$P(x_1x_2 \ldots x_n) = P(x_n|x_1x_2 \ldots x_{n-1}) \ldots P(x_2|x_1)P(x_1)$$

Can we compute it?

$$P(x_i|x_1x_2 \ldots x_{i-1}) = \frac{Count(x_1x_2 \ldots x_{i-1}x_i)}{Count(x_1x_2 \ldots x_{i-1})}$$

# Intuition:

Can we compute it?

$$P(x_i \mid x_1 x_2 \ldots x_{i-1}) = \frac{Count(x_1 x_2 \ldots x_{i-1} x_i)}{Count(x_1 x_2 \ldots x_{i-1})}$$

Sharp corners:

- Not enough data

- Long nGrams -> totally-predictable text parts -> nothing new; (some kind of overfitting)

**Any ideas?**

# Intuition:

Can we compute it?

$$P(x_i \mid x_1 x_2 \ldots x_{i-1}) = \frac{Count(x_1 x_2 \ldots x_{i-1} x_i)}{Count(x_1 x_2 \ldots x_{i-1})}$$

Any ideas?

**Markov assumption:** $P(x_i \mid x_1 \ldots x_{i-1}) = P(x_i \mid x_{i-K} \ldots x_{i-1})$

…means that current event depends on not more then K preceding one;

Example:

- **Unigram:** P(imagine there is no heaven) = P(imagine) x P(there) x … P(heaven)

- **Bigram:** P(imagine there is no heaven) = P(heaven | no) x P(no|is) x P(is|there)…

# Practical tricks:

- Most popular - trigram models; Sometimes it’s OK to use 4 or 5-grams models when there is sufficient training data;

- We will use <s> as «sentence start» and </s> as «sentence end» symbols to keep 2-grammity for first and last words.
  For trigram models sentences starts with <s><s> symbols.

- Log probabilities:

  - P(x) < 1 => P_1 * P_2 * … * P_n <<< 0

  - log(x1 * x2) = log(x1) + log(x2)

  - p1 * p2 * p3 * p4 = exp(log(p1) + log(p2) + log(p3) + log(p4))

# Berkeley Restaurant Project:

- Berkeley Restaurant Project - a dialogue system from the last century that answered questions about a database of restaurants in Berkeley;

- can you tell me about any good cantonese restaurants close by mid priced thai food is what i'm looking for
  tell me about chez panisse
  can you give me a listing of the kinds of food that are available
  i'm looking for a good place to eat breakfast
  when is caffe venezia open during the day

| | i | want | to | eat | chinese | food | lunch | spend |
|---|---|---|---|---|---|---|---|---|
| **i** | 0.002 | 0.33 | 0 | 0.0036 | 0 | 0 | 0 | 0.00079 |
| **want** | 0.0022 | 0 | 0.66 | 0.0011 | 0.0065 | 0.0065 | 0.0054 | 0.0011 |
| **to** | 0.00083 | 0 | 0.0017 | 0.28 | 0.00083 | 0 | 0.0025 | 0.087 |
| **eat** | 0 | 0 | 0.0027 | 0 | 0.021 | 0.0027 | 0.056 | 0 |
| **chinese** | 0.0063 | 0 | 0 | 0 | 0 | 0.52 | 0.0063 | 0 |
| **food** | 0.014 | 0 | 0.014 | 0 | 0.00092 | 0.0037 | 0 | 0 |
| **lunch** | 0.0059 | 0 | 0 | 0 | 0 | 0.0029 | 0 | 0 |
| **spend** | 0.0036 | 0 | 0.0036 | 0 | 0 | 0 | 0 | 0 |

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| **lunch** | 0.0059 | 0 | 0 | 0 | 0 | 0.0029 | 0 | 0 |
| **spend** | 0.0036 | 0 | 0.0036 | 0 | 0 | 0 | 0 | 0 |

- P(i|<s>) = 0.25  P(english|want) = 0.0011  (additional data)
  P(food|english) = 0.5  P(</s>|food) = 0.68

- **Can you compute** P( i want english food ) ?

# Berkeley Restaurant Project:

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- P(i|<s>) = 0.25  P(english|want) = 0.0011  (additional data)
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- P( i want english food ) = P(i|<s>) x P(want|i) x P(english|want) x P(food|english) x P(</s>|food)
  = 0.25 × 0.33 × 0.011× 0.5 ×0.68
  = .000031

# Model evaluation:

- **Extrinsic**
  Checking quality by inducing the model into a bigger useful task (machine translation, spelling correction, ...). If the target metric (where the money is: translators work time, editor's time, clicks count, earned money, etc.) goes up, the model has become better

- **Intrinsic**
  ~~Evaluation for the poor~~ we need estimates when extrinsic evaluation is too expensive or when one doesn't want the results to be related to some specific application (if the model is universal to certain extent); also a metric that shows us how 'good' the model is

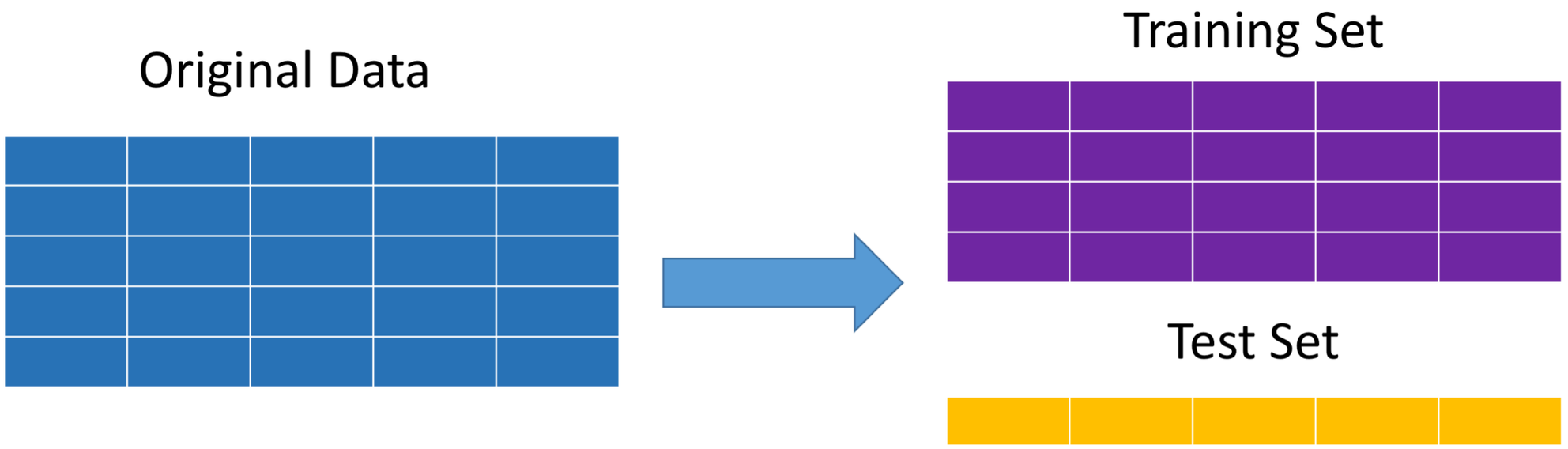
# Quality evaluation:

We have the data, we have the metric

We split the data into:

- train set (for tuning models)
- test set (for trained models evaluation)

We have to believe that train and test set data samples are from “the same distribution” (otherwise we won’t be able to train anything useful)



# Quality evaluation:

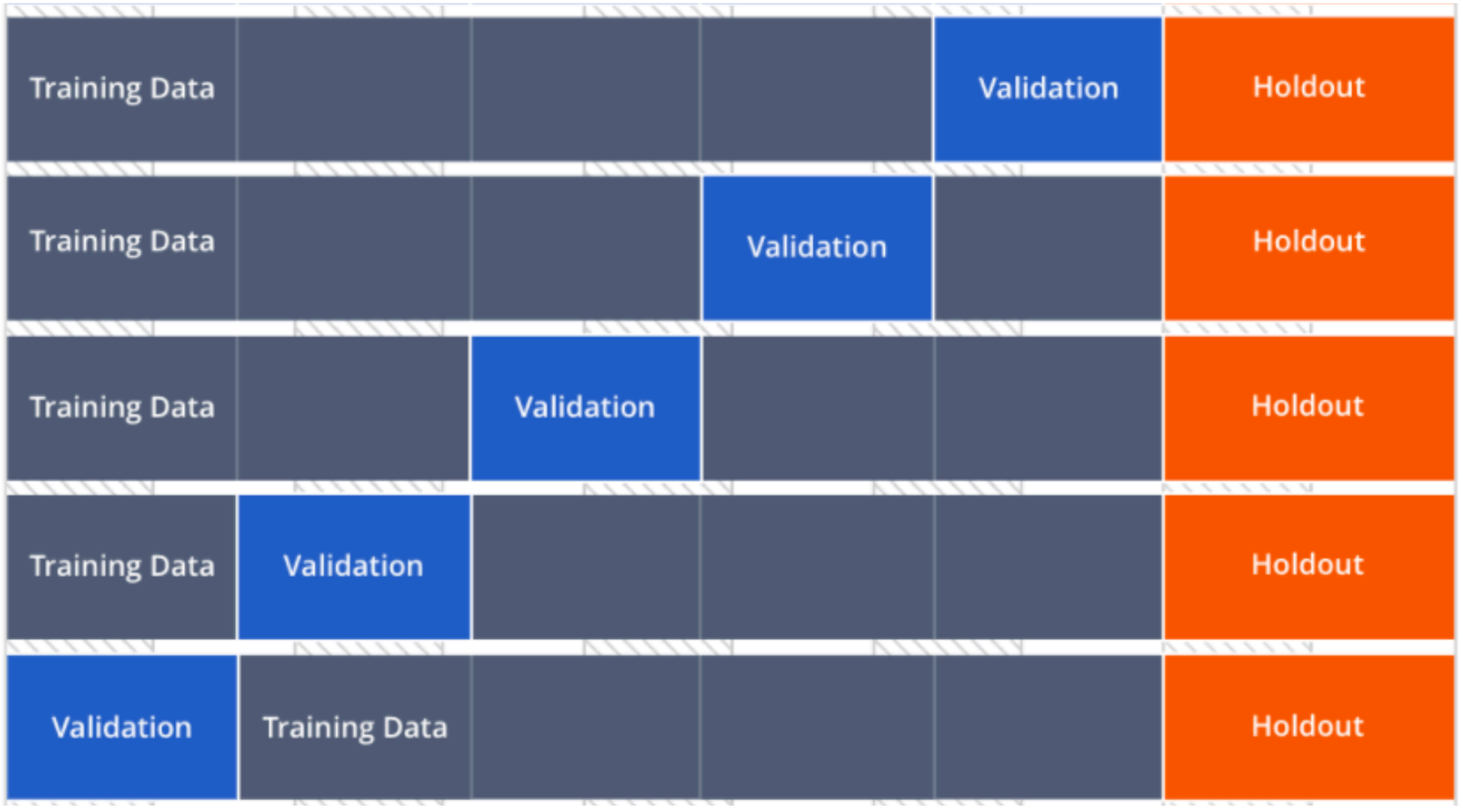

- **Deadly Sin №1**
  Test data leaks into train set (this way we lose generalization capability and estimates validity)

- **Deadly Sin №2**
  Tuning hyperparameters on test set

**But how do we tune the parameters?**
**Ideas?**

# Quality evaluation:

- K-fold scheme:
- **Train** - training model
- **Validation** - evaluating quality + analyzing errors + tuning hyperparameters
- **Holdout** - blind quality evaluation: looking at quality metric ONLY + not too often, so as not to overfit



# Perplexity:

- The large the probability of the test text, the closer the model is to life

- Perplexity — inverse probability of the text normalized by word sequence length:

$$PP(W) = P(x_1 \ldots x_N)^{-\frac{1}{N}}$$

  Is is evident the less is better;

- Looks like entropy:

$$PP(W) = P(x_1 \ldots x_N)^{-\frac{1}{N}} = e^{-\frac{1}{N}\sum_{i=1}^{N} log(P(x_i|x_1..x_{i-1}))}$$

# Quality evaluation: example

- Training on 38M tokens
- Testing on 1.5M
- Dataset: Wall Street Journal

| | 1-gram | 2-gram | 3-gram |
|---|---|---|---|
| Perplexity | 962 | 170 | 109 |

# Berkeley Restaurant Project:

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  = 0.25 × 0.33 × 0.011× 0.5 ×0.68
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- $$PP(W) = P(x_1 \ldots x_N)^{-\frac{1}{N}} = e^{-\frac{1}{N}\sum_{i=1}^{N} log(P(x_i|x_1..x_{i-1}))}$$

- **Any problems?**

# Generalization capability discussion:

- There is no such perfect corpus where all possible n-grams occur at least once!

- The model we have described returns P(x,...) = 0 when run on the text that contains at least one ngram that was not present in train set

- Evident enough, the model must generalize (and not just encode with non-zeros what was present in the train set)

  a very natural solution is to **convert zeros to small values** (a-k-a «reserve some probability for words we never met before)»

# Unknown words:

1st approach (encode it):

- **Choose** a vocabulary (word list) that is fixed in advance.
- **Convert** in the training set any word that is not in this set (any OOV word) to the unknown word token in a text normalization step.
- **Estimate** the probabilities for from its counts just like any other regular word in the training set.

2nd approach (no prior vocabulary)

- Choose K (or threshold f_min)
- Any words not from top-K by relative frequency (or with freq < f_min) -> encode with <UNK>

# Laplacian smoothing:

- So,

$$P(w_i \mid w_{i-1}) = \frac{Count(w_i, w_{i-1}) + 1}{Count(w_i) + V}$$

- If we sum over w_i - we'll see V should be the cardinality of unigrams set, otherwise P couldn't be called provability

- Doesn't work well

(too much useful weight is transferred to zero)

| | i | want | to | eat | chinese | food | lunch | spend |
|---|---|---|---|---|---|---|---|---|
| i | 0.0015 | 0.21 | 0.00025 | 0.0025 | 0.00025 | 0.00025 | 0.00025 | 0.00075 |
| want | 0.0013 | 0.00042 | 0.26 | 0.00084 | 0.0029 | 0.0029 | 0.0025 | 0.00084 |
| to | 0.00078 | 0.00026 | 0.0013 | 0.18 | 0.00078 | 0.00026 | 0.0018 | 0.055 |
| eat | 0.00046 | 0.00046 | 0.0014 | 0.00046 | 0.0078 | 0.0014 | 0.02 | 0.00046 |
| chinese | 0.0012 | 0.00062 | 0.00062 | 0.00062 | 0.00062 | 0.052 | 0.0012 | 0.00062 |
| food | 0.0063 | 0.00039 | 0.0063 | 0.00039 | 0.00079 | 0.002 | 0.00039 | 0.00039 |
| lunch | 0.0017 | 0.00056 | 0.00056 | 0.00056 | 0.00056 | 0.0011 | 0.00056 | 0.00056 |
| spend | 0.0012 | 0.00058 | 0.0012 | 0.00058 | 0.00058 | 0.00058 | 0.00058 | 0.00058 |

Probabilities for BRC with Laplacian smoothing

# Laplacian smoothing:

| | i | want | to | eat | chinese | food | lunch | spend |
|---|---|---|---|---|---|---|---|---|
| i | 3.8 | 527 | 0.64 | 6.4 | 0.64 | 0.64 | 0.64 | 1.9 |
| want | 1.2 | 0.39 | 238 | 0.78 | 2.7 | 2.7 | 2.3 | 0.78 |
| to | 1.9 | 0.63 | 3.1 | 430 | 1.9 | 0.63 | 4.4 | 133 |
| eat | 0.34 | 0.34 | 1 | 0.34 | 5.8 | 1 | 15 | 0.34 |
| chinese | 0.2 | 0.098 | 0.098 | 0.098 | 0.098 | 8.2 | 0.2 | 0.098 |
| food | 6.9 | 0.43 | 6.9 | 0.43 | 0.86 | 2.2 | 0.43 | 0.43 |
| lunch | 0.57 | 0.19 | 0.19 | 0.19 | 0.19 | 0.38 | 0.19 | 0.19 |
| spend | 0.32 | 0.16 | 0.32 | 0.16 | 0.16 | 0.16 | 0.16 | 0.16 |

Recovered frequency table for BRC

| | i | want | to | eat | chinese | food | lunch | spend |
|---|---|---|---|---|---|---|---|---|
| **i** | 5 | 827 | 0 | 9 | 0 | 0 | 0 | 2 |
| **want** | 2 | 0 | 608 | 1 | 6 | 6 | 5 | 1 |
| **to** | 2 | 0 | 4 | 686 | 2 | 0 | 6 | 211 |
| **eat** | 0 | 0 | 2 | 0 | 16 | 2 | 42 | 0 |
| **chinese** | 1 | 0 | 0 | 0 | 0 | 82 | 1 | 0 |
| **food** | 15 | 0 | 15 | 0 | 1 | 4 | 0 | 0 |
| **lunch** | 2 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
| **spend** | 1 | 0 | 1 | 0 | 0 | 0 | 0 | 0 |

Original frequency table for BRC

# Laplacian smoothing:

- Too hard for real language modeling!
- Useful for language classification task based on unigrams
- There is one fix for the Poor:

$$P(w_i \mid w_{i-1}) = \frac{Count(w_i, w_{i-1}) + \alpha}{Count(w_i) + \alpha V}$$

# Backoff and interpolation:

- **Backoff:** no occurrences of «new app SomeApp», but yet a few «new app» bigrams (if none - «unigram app»»).
  We can use probabilities of smaller n ngrams for computing estimates of probabilities for target one;

- **Interpolation:** every probability can be treated as a weighted sum of probabilities from lower n n-grams.

$$\bar{P}(w_i \mid w_{i-2}w_{i-1}) = \lambda_2 P(w_i \mid w_{i-2}w_{i-1}) + \lambda_1 P(w_i \mid w_{i-1}) + \lambda_0 P(w_i)$$

$$\sum \lambda_i = 1$$

**λ** weight are tuned on a validation set, may depend on a different context

# Kneser-Ney smoothing:

- **Absolute discount:**
  - choose bigrams, counts of which equal to k in the train set
  - look at their counts in the held out set
  - The difference ~ constant

$$P_{A.D.} = \frac{c(w_i, w_{i-1}) - d}{\sum_v C(w_{i-1}v)} + \lambda(w_i - 1)P(w_i)$$

| Bigram count in training set | Bigram count in heldout set |
|---|---|
| 0 | 0.0000270 |
| 1 | 0.448 |
| 2 | 1.25 |
| 3 | 2.24 |
| 4 | 3.23 |
| 5 | 4.21 |
| 6 | 5.23 |
| 7 | 6.21 |
| 8 | 7.21 |
| 9 | 8.26 |

- The intuition is that since we have good estimates already for the very high counts, a small discount d won't affect them much. It will mainly modify the smaller counts, for which we don't necessarily trust the estimate anyway

Refs: Kneser, R. and Ney, H. (1995); Gale, W. A. and Church, K. W. (1994). What is wrong with adding one?.

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$$P_{A.D.} = \boxed{\frac{c(w_i, w_{i-1}) - d}{\sum_v C(w_{i-1}v)}} + \boxed{\lambda(w_i - 1)P(w_i)}$$

Discount Interpolation

- Why should we interpolate?

Refs: Kneser, R. and Ney, H. (1995); Gale, W. A. and Church, K. W. (1994). What is wrong with adding one?.

# Kneser-Ney interpolation:

$$P_{A.D.} = \boxed{\frac{c(w_i, w_{i-1}) - d}{\sum_v C(w_{i-1}v)}} + \boxed{\lambda(w_{i-1})P(w_i)}$$

Discount Interpolation

- I can't see anything without my reading ____;
- reading **X** - unseen context so we are let's try to get more info from unigram model;
- *glasses? Kong?*
- *Glasses* is more rare then *Kong* cause *Hong Kong* is very frequent, but we met *Kong* only in one context - *Hong Kong.*
- P_continuation - "How likely is w to appear as a novel continuation?"»

$$P_{continuation} = \frac{|\{v : C(wv) > 0\}|}{|\{(u', w') : C(u', w') > 0\}|}$$

- The words with a poor contexts such as *Kong* will receive a much lower P_cont estimation than rich-context word *glasses.*

# Kneser-Ney interpolation:

$$P_{A.D.} = \boxed{\frac{c(w_i, w_{i-1}) - d}{\sum_v C(w_{i-1} v)}} + \boxed{\lambda(w_{i-1}) P_{continuation}(w_i)}$$

Discount

Interpolation

- Is everything clear?

$$P_{continuation} = \frac{|\{v : C(wv) > 0\}|}{|\{(u', w') : C(u', w') > 0\}|}$$

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Discount

Interpolation

- Is everything clear?
- Haha, nope! **What is λ ?**

$$P_{continuation} = \frac{|\{v : C(wv) > 0\}|}{|\{(u', w') : C(u', w') > 0\}|}$$

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Discount

Interpolation

- Is everything clear?
- Haha, nope. What is λ ?

$$P_{continuation} = \frac{|\{v : C(wv) > 0\}|}{|\{(u', w') : C(u', w') > 0\}|}$$

- Tricky normalization to turn our P_continuation from direct «absolute» probability space into it’s place into «reserved discounted» probability mass;

$$\lambda(w_{i-1}) = \frac{d}{\sum_v C(w_{i-1} v)} |\{w : C(w_{i-1} w) > 0\}|$$

# Kneser-Ney interpolation:

$$P_{A.D.} = \boxed{\frac{c(w_i, w_{i-1}) - d}{\sum_v C(w_{i-1}v)}} + \boxed{\lambda(w_{i-1})P_{continuation}(w_i)}$$

Discount

Interpolation

- **λ:** tricky normalization to turn our P_continuation from direct «absolute» probability space into it's place into «reserved discounted» probability mass;

$$P_{continuation} = \frac{|\{v : C(wv) > 0\}|}{|\{(u', w') : C(u', w') > 0\}|}$$

- **Is everything clear now?**

$$\lambda(w_{i-1}) = \frac{d}{\sum_v C(w_{i-1}v)} |\{w : C(w_{i-1}w) > 0\}|$$

# Kneser-Ney:

$$P_{A.D.} = \boxed{\frac{c(w_i, w_{i-1}) - d}{\sum_v C(w_{i-1} v)}} + \boxed{\lambda(w_{i-1}) P_{continuation}(w_i)}$$

Discount

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- **λ:** tricky normalization to turn our P_continuation from direct «absolute» probability space into it's place into «reserved discounted» probability mass;

$$P_{continuation} = \frac{|\{v : C(wv) > 0\}|}{|\{(u', w') : C(u', w') > 0\}|}$$

- Is everything clear now?

$$\lambda(w_{i-1}) = \frac{d}{\sum_v C(w_{i-1} v)} |\{w : C(w_{i-1} w) > 0\}|$$

- **Nope! What about higher N?**

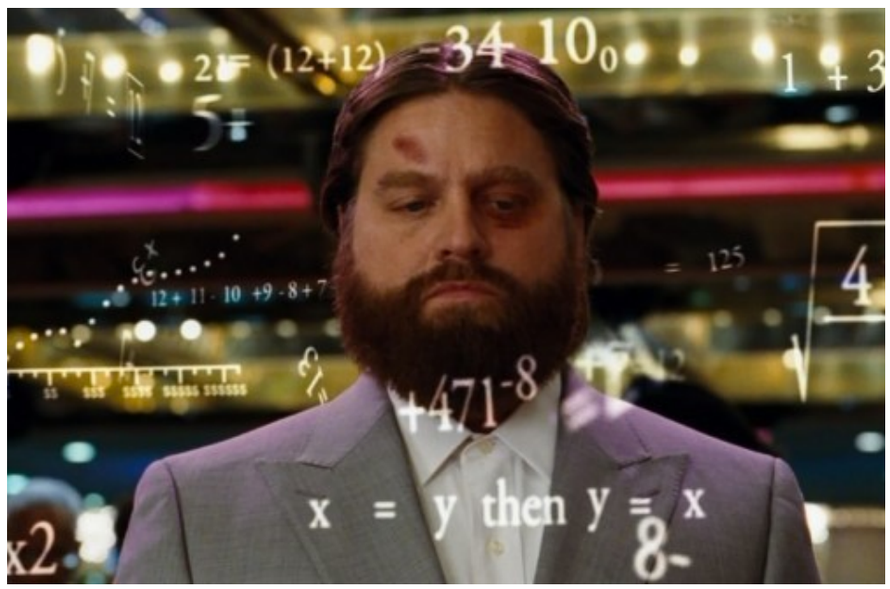
]

$$P_{\text{KN}}(w_i|w_{i-n+1}^{i-1}) = \frac{\max(c_{KN}(w_{i-n+1}^{i}) - d, 0)}{\sum_v c_{KN}(w_{i-n+1}^{i-1} v)} + \lambda(w_{i-n+1}^{i-1}) P_{KN}(w_i|w_{i-n+2}^{i-1}) \quad (3.37)$$

where the definition of the count $c_{KN}$ depends on whether we are counting the highest-order n-gram being interpolated (for example trigram if we are interpolating trigram, bigram, and unigram) or one of the lower-order n-grams (bigram or unigram if we are interpolating trigram, bigram, and unigram):

$$c_{KN}(\cdot) = \begin{cases} \text{count}(\cdot) & \text{for the highest order} \\ \text{continuationcount}(\cdot) & \text{for lower orders} \end{cases} \quad (3.38)$$

**Look at Jufarsky book**



# Summary:

Evaluation of smoothing methods:

Perplexity for language models trained on the Europarl corpus

| **Smoothing method** | **bigram** | **trigram** | **4-gram** |
|---|---|---|---|
| Good-Turing | 96.2 | 62.9 | 59.9 |
| Witten-Bell | 97.1 | 63.8 | 60.4 |
| Modified Kneser-Ney | 95.4 | 61.6 | 58.6 |
| Interpolated Modified Kneser-Ney | 94.5 | 59.3 | 54.0 |

**Based on Phillips Koehns slides**

# Data:

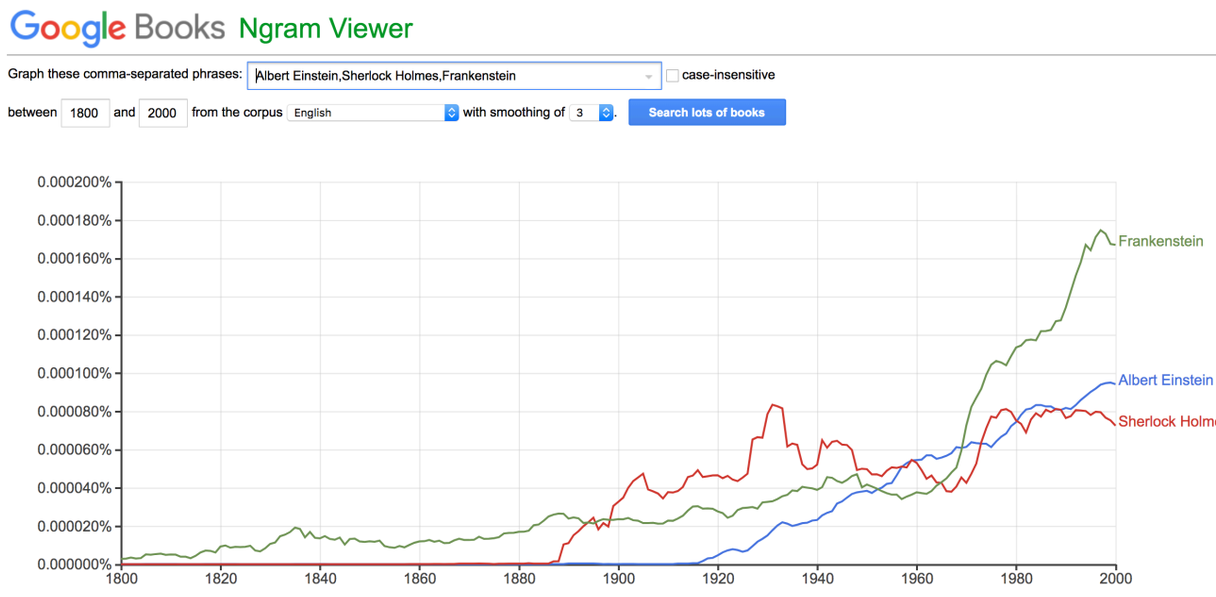
- Russian National Corpus: http://www.ruscorpora.ru/corpora-freq.html

- Google books ngrams: python package raw data

- *Huge unlabeled texts collection for your specific task

- The whole Internet

| | | |
|---|---|---|
| Словоформы | zip-архив (5,5 Мб, обрезаны по частоте 3) | топ-100 |
| 2-граммы | zip-архив (39 Мб, обрезаны по частоте 3) | топ-100 |
| 3-граммы | zip-архив (31 Мб, обрезаны по частоте 3) | топ-100 |
| 4-граммы | zip-архив (44 Мб, обрезаны по частоте 2) | топ-100 |
| 5-граммы | zip-архив (28 Мб, обрезаны по частоте 2) | топ-100 |
| 6-граммы | | топ |



# Tools:

- nltk has some LM-related code (nltk.models)
- Here's what Moses can use (open source SMT engine)

Our decoder works with the following language models:

- the SRI language modeling toolkit, which is freely available.
- the IRST language modeling toolkit, which is freely available and open source.
- the RandLM language modeling toolkit, which is freely available and open source.
- the KenLM language modeling toolkit, which is included in Moses by default.
- the DALM language modeling toolkit, which is freely available and open source.
- the OxLM language modeling toolkit, which is freely available and open source.
- the NPLM language modeling toolkit, which is freely available and open source.