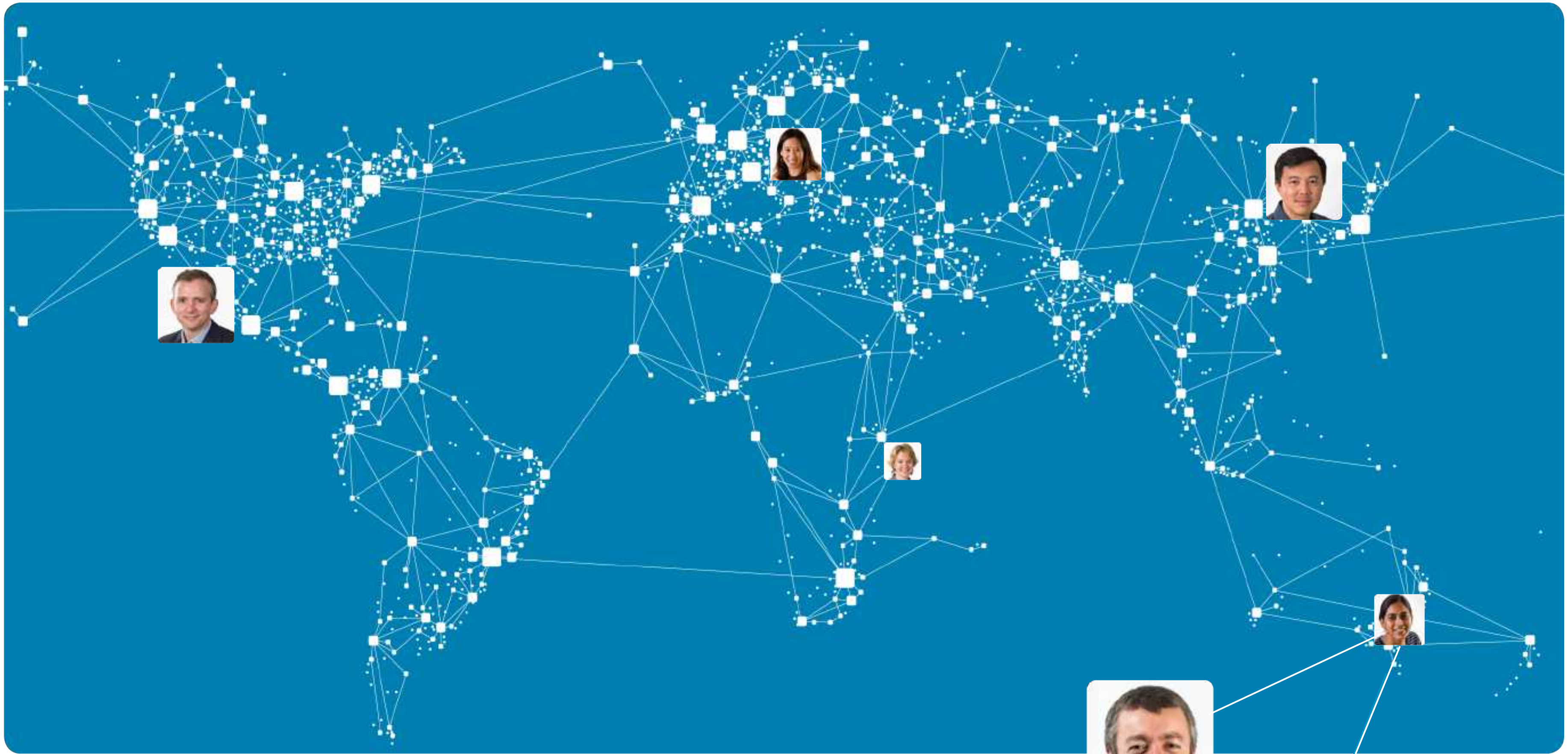

High-Precision Phrase-Based Document Classification on a Modern Scale

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Leap into the future

- Who predicted in 1990 that all of us would have cell phones by 2000?
- Who predicted in 2000 that all of us would have GPS devices by 2010?
  - *http://www.cs.technion.ac.il/~ronb/city.html*
- Here's my prediction:
  - By 2020, we all will carry devices that record audio (video?) 24/7
  - And transmit the recorded data instantly to a cloud storage locker
- Why?
  - Personal security
  - "Perfect" memory
- Wanna analyze this data? Slice it? ☺
  - E.g., what are Libyans talking about today?
- The best approximation of "objectivity"

Simple arithmetic

- 1 billion people × 1 gigabyte of audio per day = 1 exabyte
  - 1 zettabyte in 3 years
- 1 billion people × 1K utterances a day × 100 bytes of text = 100 terabytes
  - Assuming that speech recognition works ☺

- Lexicon of an average person is ~10,000 words (or “concepts”)
  - Concepts are mostly overlapping in all languages
- 1 trillion utterances a day built from a 10K word set
  - How much repetition do we have?

The task

- Categorize 1 trillion **short documents** (utterances?) by topic
- Allow **multi-labeling**
- Allow **reject option** ("this utterance doesn't belong to any category")

- <10 words on average per utterance is not too much content
- Most of the signal sits in a few phrases (*noun phrases*?) per utterance
- **Classify phrases and get utterance classification for free**
  - (Semi-)manual labeling of phrases would be most accurate
  - English only (assuming machine translation works ☺)

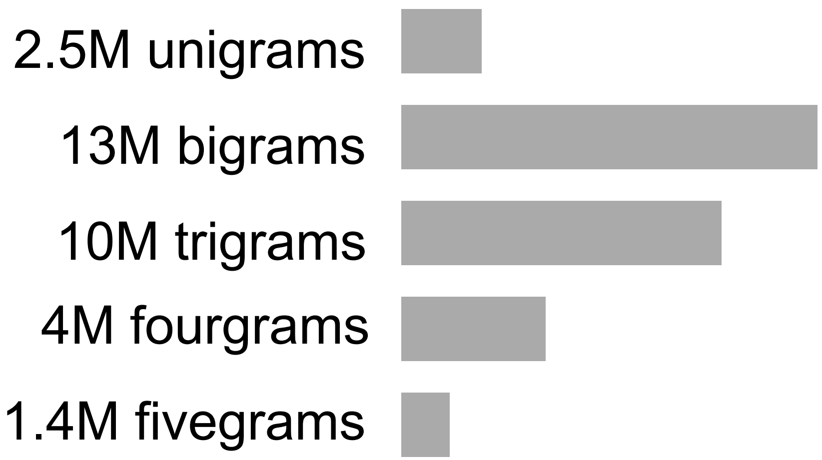
- Example: "*~~How many~~ presents ~~have you got to~~ buy ~~yet~~*?"
  - Assign a phrase "*buy presents*" into the category "Shopping"

A $1M question: how many phrases to label?

- Our finding: not too many ☺
- Naively, the number of bigrams composed of 10K words is $10K^2$ = 100M
  - Forget about trigrams, fourgrams etc ☺
- But not all those phrases are common in the language!
  - Labeling low-frequency phrases is not cost effective
- **Number of common phrases composed of 10K words is under 1M**
  - Assuming 1¢ per phrase, you spend $10K (+fees) to label all of them
  - And two weeks of work ☺

Where did we take the data from?

- We took phrase counts from the Web1T data
  - Web1T has ngram counts from a one-trillion-word data collection
- Preprocessing:
  - Filtered out ngrams that appeared <1000 times in Web1T
  - Removed stopwords from all ngrams
  - Lower-cased all words
  - Ignored word order (by sorting words in an ngram)
- Example: “*all Words from the Dictionary*” → “*dictionary words*”
- Resulting dataset:



Which phrases are considered common?

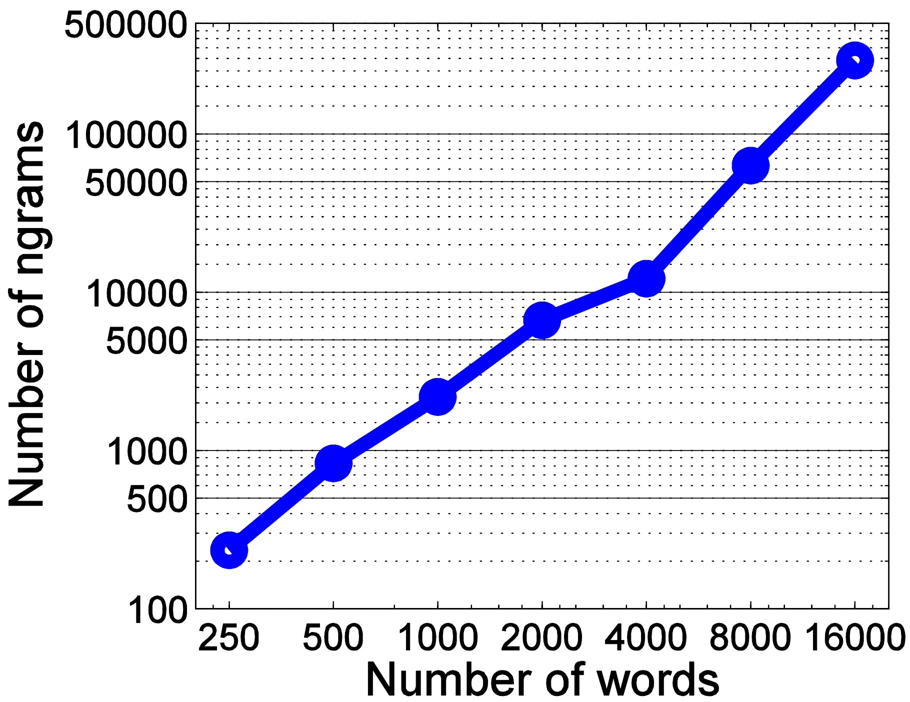
- Define frequency F of a set X as frequency of its least frequent item:

$$F(X) = \min_{x \in X} F(x)$$

- Given a set of words W and a set of phrases T composed of words W we say that $\boldsymbol{T}$ **is frequent enough if** $\boldsymbol{F(T) \geq F(W)}$
  - T is as frequent as the set of words it was composed of

- We want to find an upper bound on the size $|T|$ as a function of $|W|$

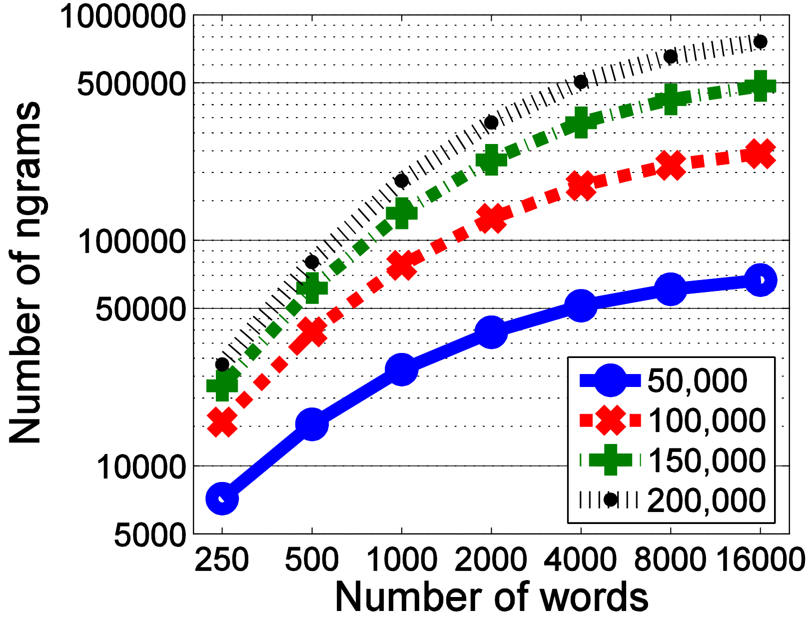
Number of phrases: unrealistic setup

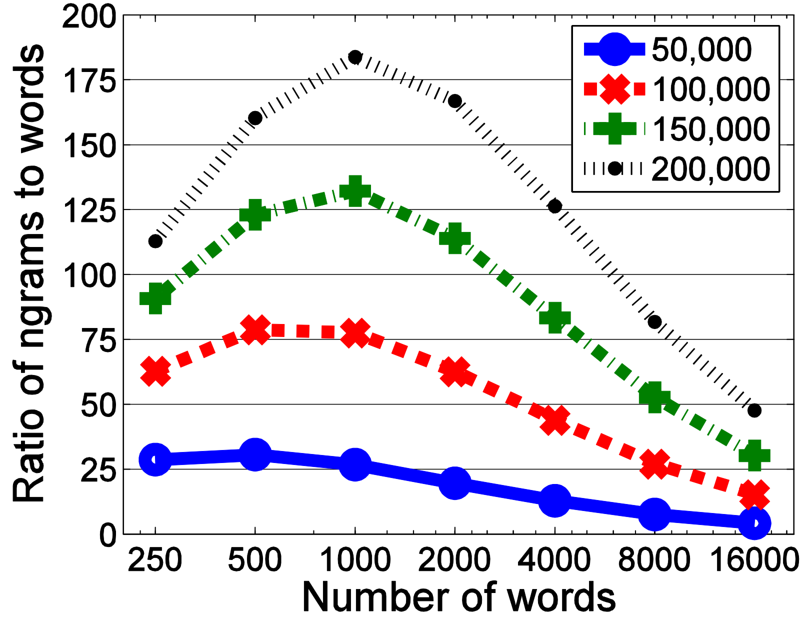


- Take n most common phrases
- Identify k words out of which those phrases were composed
- Take all n^* common phrases composed out of those k words
- Plot n^* as a function of k

- **Result: $n^* = k^\alpha$ where α is small**
  - $1 \leq \alpha \leq 1.3$
- Number of phrases is under 0.5M

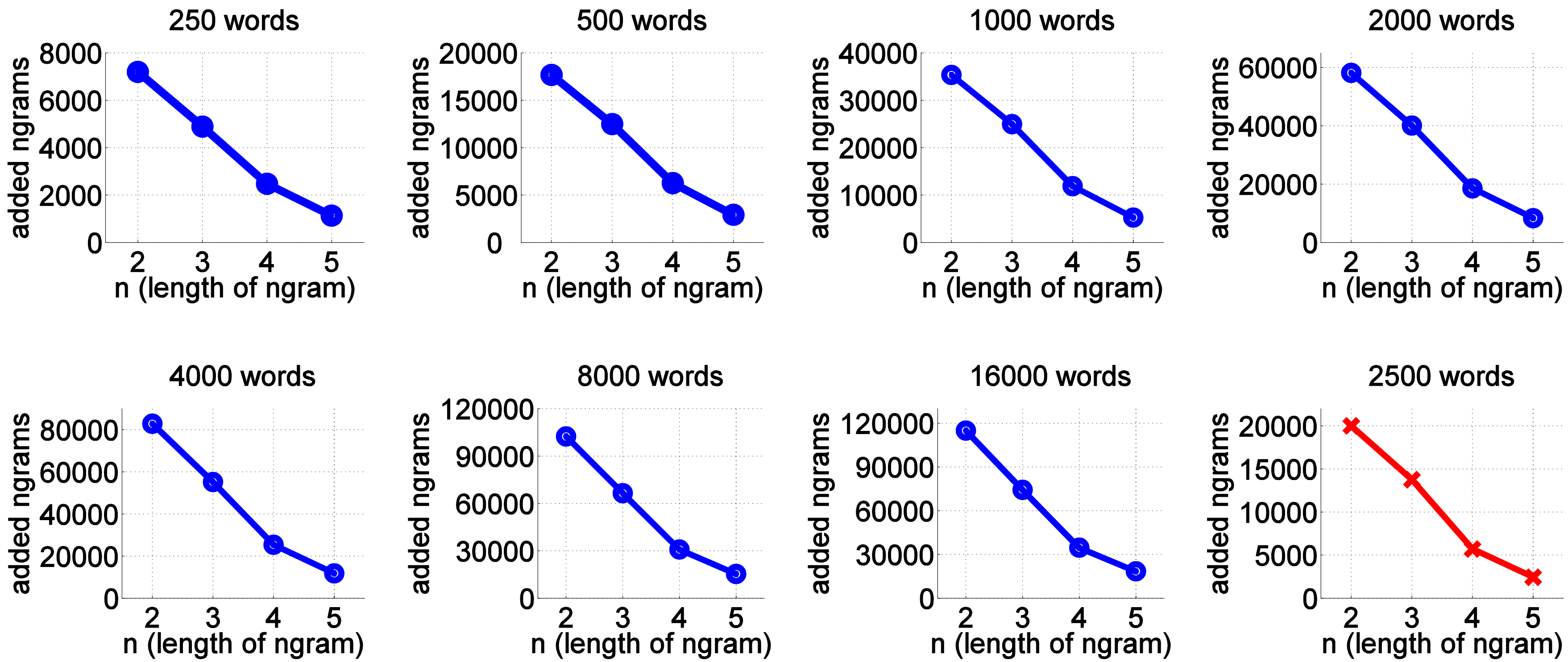
Number of phrases: more realistic setup





- In classification by topic, we mostly care about topical words
- Compose a set of words W that are topically related
  - Sampled from the most common 50K, 100K, 150K, or 200K words
- **Number of frequent enough phrases stays under 1M**

Web1T data is sufficient



- Sixgrams (and longer) won't contribute too many common phrases
- The last graph is over the real-world controlled vocabulary

For text datasets of any size, there won't be too many common phrases to label

Phrase-based classification: formal requirements

- Classify **short** pieces of text (short documents)
  - Tweets, news headlines, Quora questions, helpdesk inquiries etc
- To a **small** number of categories
- The number of documents can be **huge** (billions? trillions?)
- Precision requirements are **high**: 95% and up
- Coverage should be **acceptable**
  - Some documents may remain uncategorized

Makes our life easier

Makes our life harder

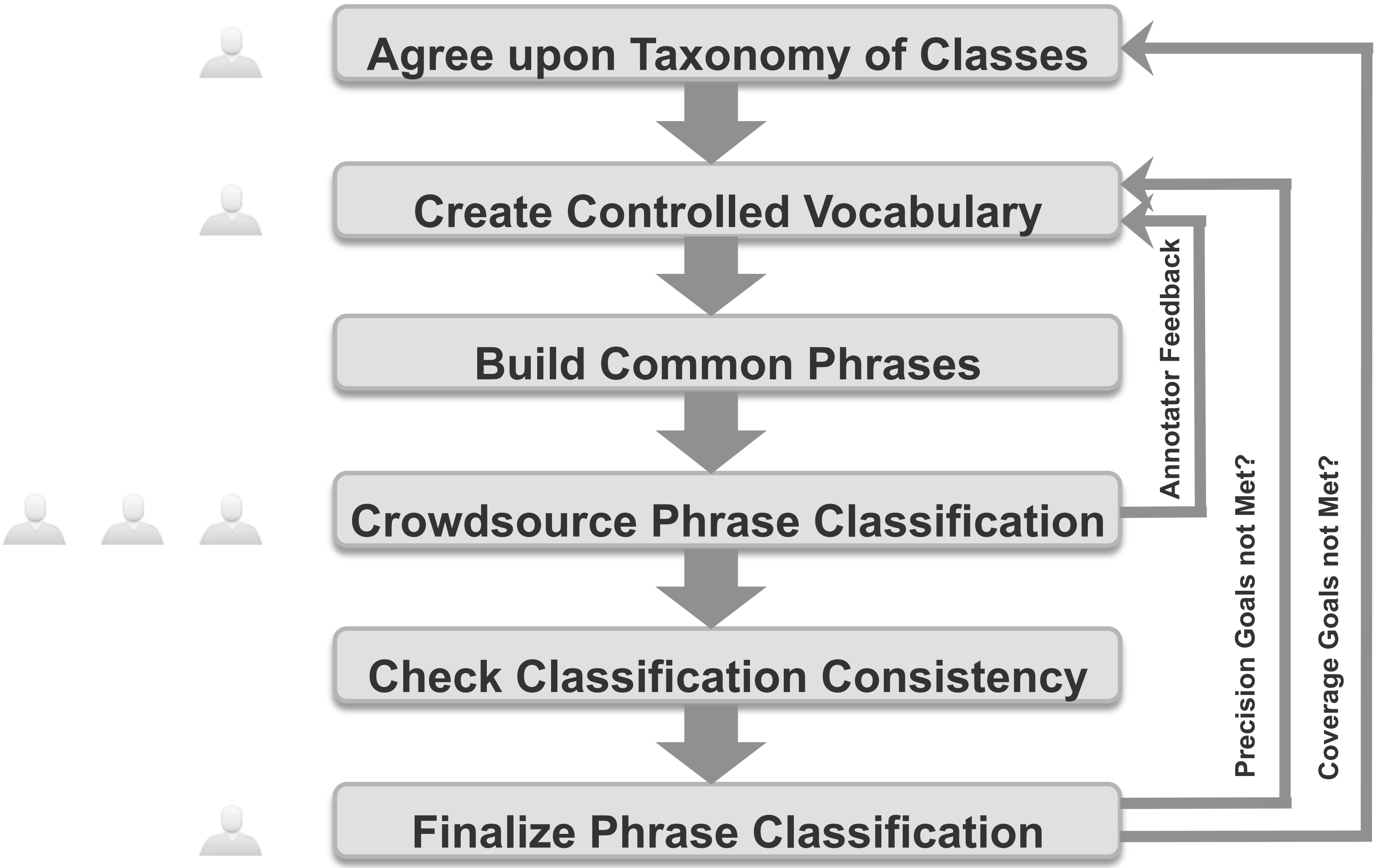
‘Short document’ constraint relaxation

- Phrase-based classification may work **not only on short documents**
- Documents may be long but most of their topicality is in a few phrases

- Define $\mathrm{I}(D;C)$ the Mutual Information between docs D and their classes C
- Define $\mathrm{I}(T;C)$ the Mutual Information between phrases T and classes C

- Data Processing Inequality: $\mathrm{I}(D;C) \geq \mathrm{I}(T;C)$
- Phrases are ***near sufficient*** if $\mathrm{I}(T;C) \geq (1\text{-}\varepsilon)\ \mathrm{I}(D;C)$ for a small ε
- On our test set: $\dfrac{\mathrm{I}(T;C)}{\mathrm{I}(D;C)} = 0.92$ however $\dfrac{\mathrm{I}(W;C)}{\mathrm{I}(D;C)} = 0.53$
  - Much more information in phrases than in single words

How to classify phrases



Phrase classification step by step

- **Agree upon Taxonomy of Classes:**
  - Too bad if the chosen classes don't represent the data D
- **Create Controlled Vocabulary:**
  - From a list of most common words in D, choose topical words W
- **Build common phrases:**
  - Out of words W, construct all phrases that appear in D
  - Choose the set T of most common phrases
  - Filter out compound phrases (e.g. "*machine learning and physics*")
  - Filter out too specific phrases ("*content-based collaborative filtering*")
  - Filter out near redundant phrases (remove "*recommendation systems*", leave "*recommender systems*")

Crowdsource Phrase Classification

- Educate the workers about the task
- **Multi-labeling**: Each phrase will be assigned to zero, one, or more classes
- Each phrase should be categorized by a number of workers
  - Use a voting mechanism to decide on a category

Check Classification Consistency

- Build a representation of each phrase t, as an aggregation of all documents t belongs to
  - May add more information if available
- Using those representations, find k most similar phrases to each t
- Mark t as 'suspicious' if $C(t) \neq C_{\text{knn}}(t)$
- Over all non-suspicious phrases, learn a linear SVM
- For each suspicious t, choose either $C(t) = C_{\text{svm}}(t)$ or $C_{\text{knn}}(t) = C_{\text{svm}}(t)$
  - If $C(t) \neq C_{\text{knn}}(t) \neq C_{\text{svm}}(t)$, leave t uncategorized
- Finalize phrase classification
  - Spot-check the resulting classification

Phrase-based classification is simple

- Given a document d and a list of categorized phrases T
- Find all phrases from T that appear in d: $T_d = d \cap T$
  - Use shallow NLP to filter out some irrelevant phrases
- Assign d to all classes to which T_d belongs: $C(d) = \bigcup_{t \in T_d} C(t)$

Deployed system: Job Title Classification

- About 100M job titles, a couple of dozen classes
- **Built a controlled vocabulary** of about 2500 words
  - Profession names, seniority words, and job function words
  - Mapped abbreviations, common misspellings, and foreign words onto the vocabulary words
- **Constructed most common phrases** (about 20K of them)
  - Removed compound, too specific, and redundant phrases
- **Crowdsourced phrase classifications**
  - Used two teams of LinkedIn employees
  - About 15% didn't gain the majority vote, which got relabeled
- About 25% titles were categorized inconsistently with the kNN model
  - Run SVM on them – resolved almost all issues
- Final spot-checking was quite helpful too

Evaluation framework: comparison with SVM

- Once all documents got categorized, we got a 100M labeled collection
  - 95% precision, 80% coverage
- We choose 20K documents and trained an SVM on them
  - Tested over all 100M titles
- Tried 4 options for choosing the training set
  - (a) The categorized phrases T
  - (b) T with word translations
  - (c) Most frequent titles
  - (d) Randomly chosen titles
- Reporting 2 quality measures:
  - Partial match in the assigned classes between our method and SVM
  - Full match in the assigned classes between our method and SVM

Results

Setup	Partial Match			Full Match		
	Precision	Recall	F-measure	Precision	Recall	F-measure
(a)	91.2%	83.6%	87.2%	80.9%	65.5%	72.4%
(b)	94.0%	92.1%	93.0%	82.4%	73.6%	77.8%
(c)	95.4%	88.2%	91.7%	83.0%	73.4%	77.9%
(d)	95.1%	88.0%	91.4%	80.7%	73.7%	77.1%

- 90 percentile means that phrase-based classification and SVM are not too different
  - Which looks true if we match only one class
- It is not true if we match all classes in the multi-labeled setup
  - Humans are good at assigning documents to more than one class

Conclusion

- Proposed a general framework for classifying large document collections
  - If the “near-sufficiency” property folds (documents are short)
- The process is semi-manual with a heavy-lift consistency check
  - **The consistency check boosts precision by ~20%**

- Showed that regardless the size of the data, the semi-manual process is feasible
- Looking forward to categorizing trillions of utterances
  - See you all in 2020 ☺