How much data is enough?
Predicting accuracy on large datasets from smaller pilot data

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Outline

Introduction

Empirical models of accuracy vs training data size

Accuracy extrapolation task

Conclusions and future work
ML as an engineering discipline

- A mature engineering discipline should be able to predict the cost of a project before it starts.
- Collecting/producing training data is typically the most expensive part of an ML or NLP project.
- We usually have only the vaguest idea of how accuracy is related to training data size and quality.
  - More data produces better accuracy.
  - Higher quality data (closer domain, less noise) produces better accuracy.
  - But we usually have no idea how much data or what quality of data is required to achieve a given performance goal.
- Imagine if engineers designed bridges the way we build systems!

See statistical power analysis for experimental design, e.g., Cohen (1992).
Goals of this research project

• Given desiderata (accuracy, speed, computational and data resource pricing, etc.) for an ML/NLP system, design a system that meets these.

• Example: design a semantic parser for a target application domain that achieves 95% accuracy across a given range of queries.
  ▶ What hardware/software should I use?
  ▶ How many labelled training examples do I need?

• Idea: Extrapolate performance from small pilot data to predict performance on much larger data
What this paper contributes

- Studies different methods for predicting accuracy on a full dataset from results on a small pilot dataset
- We propose new *accuracy extrapolation task*, provide results for the 9 extrapolation methods on 8 text corpora
  - Uses the *fastText document classifier* and corpora (Joulin et al., 2016)
- Investigates *three extrapolation models* and *three item weighting functions* for predicting accuracy as a function of training data size
  - Easily inverted to estimate training size required to achieve a target accuracy
- Highlights the importance of *hyperparameter tuning* and *item weighting* in extrapolation
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Overview

- **Extrapolation models** of how error $e (= 1 - \text{accuracy})$ depends on training data size $n$
  - *Power law:* $\hat{e}(n) = bn^c$
  - *Inverse square-root:* $\hat{e}(n) = a + bn^{-1/2}$
  - *Biased power law:* $\hat{e}(n) = a + bn^c$

- Extrapolation model estimated from multiple runs using *weighted least squares regression*
  - Model trained on *different-sized subsets of pilot data*
  - Same test set is used to evaluate each run
  - The evaluation of each model training/test run is a training data point for extrapolation model

- **Weighting functions** for least squares regression
  - *Constant weight* $(1)$
  - *Linear weight* $(n)$
  - *Binomial weight* $(n/e(1 - e))$

See e.g., Haussler et al. (1996); Mukherjee et al. (2003); Figueroa et al. (2012); Beleites et al. (2013); Hajian-Tilaki (2014); Cho et al. (2015); Sun et al. (2017); Barone et al. (2017); Hestness et al. (2017)
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Accuracy extrapolation task

<table>
<thead>
<tr>
<th>Corpus</th>
<th>Labels</th>
<th>Train (K)</th>
<th>Test (K)</th>
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- FastText document classifier & data
  - 4 development corpora
  - 4 evaluation corpora
  - Joulin et al. (2016)’s train/test division
- Pilot data is 0.5 or 0.1 of train data
- Goal: use pilot data to predict test accuracy when trained on full train data
Extrapolation on ag_news corpus

- Extrapolation with *biased power-law model* $(\hat{e}(n) = a + bn^c)$ and *binomial weights* $(n/e(1 - e))$
- Extrapolation from 0.5 training data is generally good
- Extrapolation from 0.1 training data is poor unless *hyperparameters are optimised at each subset of pilot data*
Relative residuals ($\hat{e}/e - 1$) on dev corpora

Extrapolation

- $b*n^c$
- $a+b*n^{-1/2}$
- $a+b*n^c$

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<th>Extrapolation</th>
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<th>amazon_review_full</th>
<th>dbpedia</th>
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1 n n/e*(1−e) 1 n n/e*(1−e) 1 n n/e*(1−e) ... 5

-0.075
-0.050
-0.025
0.000
-0.03
-0.02
-0.01
0.00
-0.02
-0.01
0.00
RMS relative residuals on test corpora

<table>
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<th>sogou news</th>
<th>yahoo answers</th>
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• Based on dev corpora results, use:
  - biased power law model ($\hat{e}(n) = a + bn^c$)
  - binomial item weights ($n/e(1 - e)$)

• Evaluate extrapolations with RMS of relative residuals ($\hat{e}/e - 1$)

• Larger pilot data $\Rightarrow$ smaller extrapolation error

• Optimise hyperparameters at each pilot subset $\Rightarrow$ smaller extrapolation error
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• The field need methods for predicting how much training data a system needs to achieve a target performance.
• We introduced an *extrapolation task* for predicting a classifier’s accuracy on a large dataset from a small pilot dataset.
• Highlight the importance of *hyperparameter tuning* and *item weighting*.
• Future work: *extrapolation methods that don’t require expensive hyperparameter optimisation*. 
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References


