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 for 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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</tbody>
</table>

- **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 \( \frac{n}{e(1 - e)} \)
- 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

- \(b*n^c\)
- \(a+b*n^{-1/2}\)
- \(a+b*n^c\)

Graphs showing the relative residuals for different data sets and extrapolation models.
RMS relative residuals on test corpora

<table>
<thead>
<tr>
<th>Pilot data</th>
<th>amazon review polarity</th>
<th>sogou news</th>
<th>yahoo answers</th>
<th>yelp review full</th>
<th>Overall</th>
</tr>
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<td>0.0519</td>
<td>0.0496</td>
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<td><strong>0.0200</strong></td>
</tr>
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</table>

- Based on dev corpora results, use:
  - biased power law model \( \hat{e}(n) = a + bn^c \)
  - binomial item weights \( \frac{n}{e(1 - e)} \)
- Evaluate extrapolations with RMS of relative residuals \( \frac{\hat{e}}{e - 1} \)
- 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


