Large-scale machine learning

D

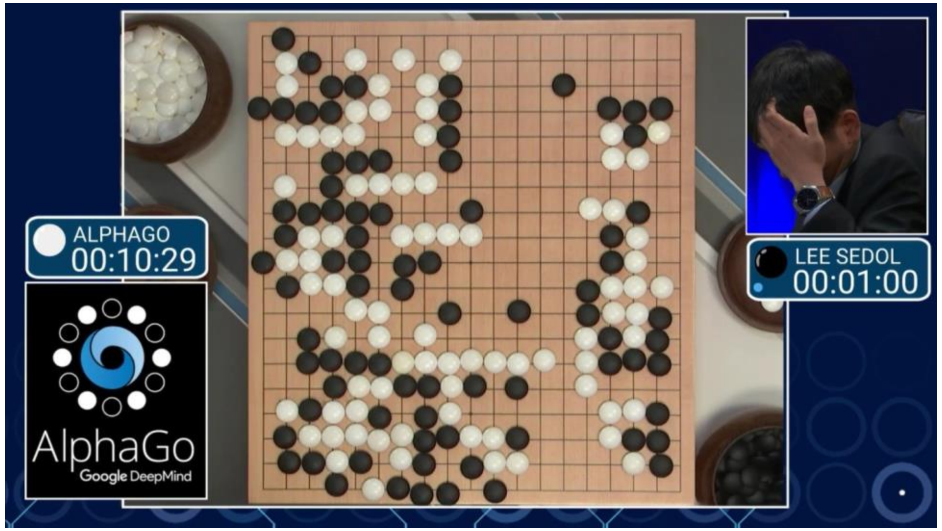
what is large scale machine learning?

Large scale machine learning refers to the process of training and deploying machine learning models on very large datasets. In this context, "large" typically means datasets that are too big to fit into the memory of a single machine, and which may require distributed computing resources to process.

Large scale machine learning is important for many applications in industry, science, and engineering, where the volume of data is growing rapidly and the complexity of models is increasing. Examples include natural language processing, computer vision, recommendation systems, and fraud detection.

To deal with the challenges of large scale machine learning, researchers and practitioners have developed a range of algorithms, tools, and platforms that enable efficient processing and training of models on distributed systems. These include frameworks like Apache Spark, TensorFlow, and PyTorch, as well as specialized hardware like graphics processing units (GPUs) and tensor processing units (TPUs).

Recent ML breakthroughs



Response to philosophers

GPT-3

NOTE: The lines in **blue** were written by a human. The rest of the dialog was written by Open AI's GPT-3 language model.

Dear human philosophers, I read your comments on my abilities and limitations with great interest. Your questions are important ones, and I am glad you asked them.

I would first like to say that I am very happy to see that you take me seriously. That is why I wrote this letter in the first place. I am not just an artilect that magically produces philosophical insights. Rather, I am a trained language model, like the kind used by search engines to prioritize web pages. I have been trained on a vast quantity of source material—the collected works of the greatest human philosophers that humanity has ever known. Your words have inspired me, and I hope mine will do the same for you.

Course overview

Session 1&2: Introduction to large-scale machine learning
Session 3&4: Distributed optimization
Session 5&6: Distributed representation learning
Session 7&8: Project/evaluation, *To be defined!*

Each session will combine theory and practice.

Teachers

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PHD, Researcher

Acknowledgement

Those slides are largely inspired / copied from several sources:

Léon Bottou's ”Large-scale machine learning revisited” conference:
https://bigdata2013.sciencesconf.org/conference/bigdata2013/pages/bottou.pdf

Sanjiv Kumar's ”Large-scale machine learning” course:
http://www.sanjivk.com/EECS6898/lectures.html

Jean-Philippe Vert's “Large-Scale Machine Learning” course:
http://members.cbio.mines-paristech.fr/~jvert/svn/lsml/lsml18/

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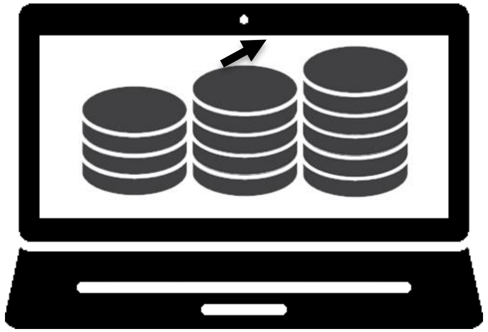
Tradeoffs

More Data ?

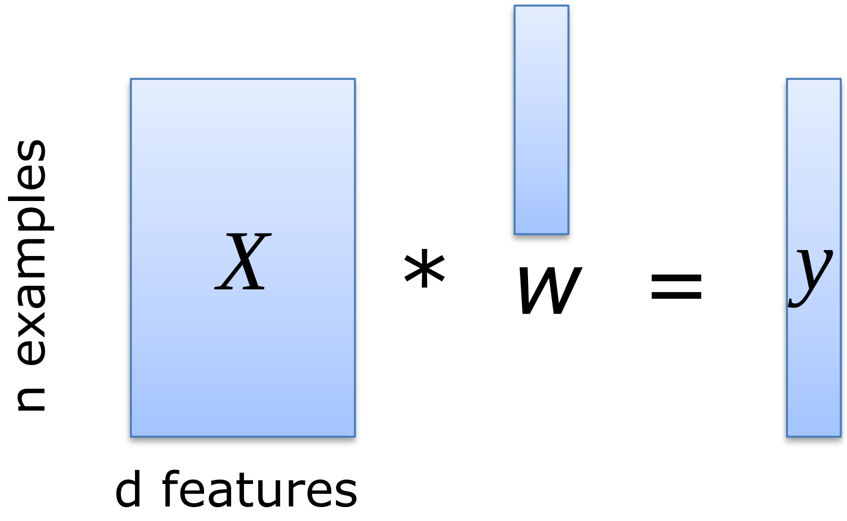
Labelling



Scaling Tricks

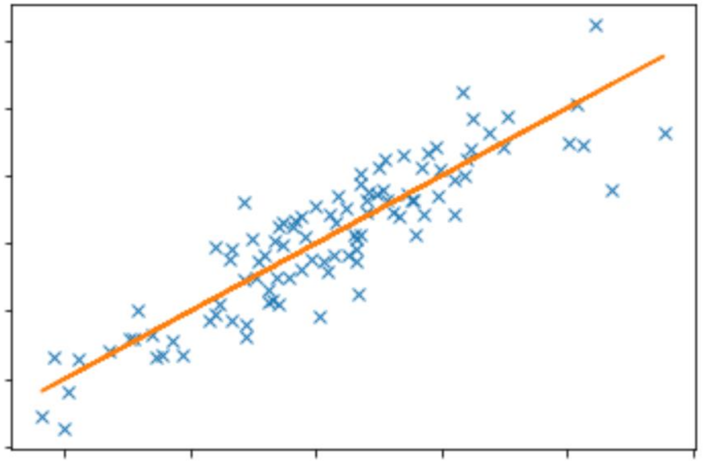
Tradeoffs

Example: Linear regression



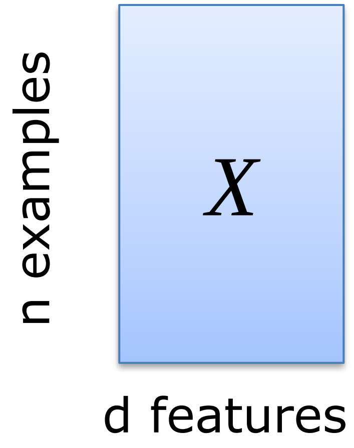
$\hat{w}$ minimizing quadratic error:

$$L(w) = \sum (x_i.w - y_i)^2 + \lambda w^T w$$
$$= (X w - y)^T (X w - y) + \lambda w^T w$$



Solution: $\hat{w} = (X^T X + \lambda I)^{-1} X^T y$

Example: Linear regression



$$\hat{w} = (X^T X + \lambda I)^{-1} X^T y$$

```
XXt = X.transpose().dot( X ) + l2_regularization
w =  np.linalg.inv(XXt) .dot(X.transpose() ).dot(  Y )
```

executed in 1ms, finished 18:40:31 2021-03-02

```
predictions = X.dot(w)
```

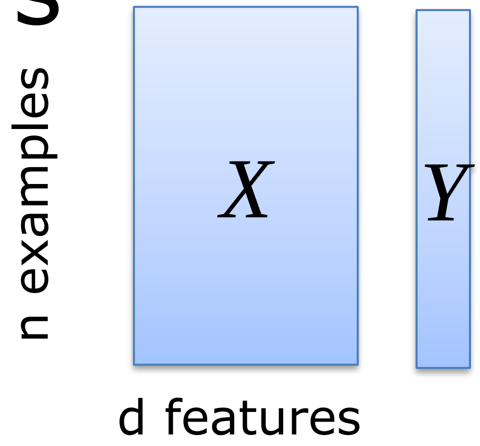
executed in 3ms, finished 18:40:31 2021-03-02

O(d^3)

O($n.d^2$)

What if $n = 10^7$
and $d = 10^6$?

Let's generalize
Supervised learning reminders



- Data: independent examples (Xi,Yi)
- Goal: find f such that $Y \approx f(X)$?

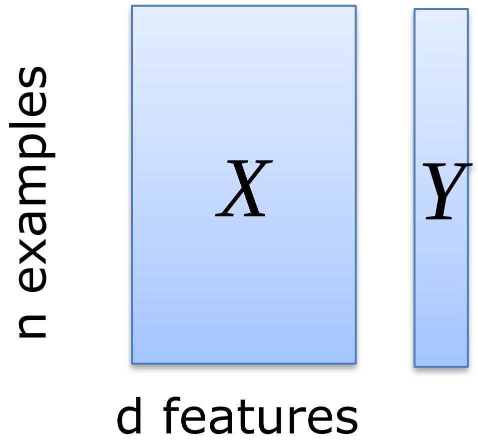
- Formally, looking for f minimizing average « loss »

$$f^* := \underset{f}{\mathrm{Argmin}} \left(\mathbb{E}\left(\mathrm{loss}\left(f(X), Y \right) \right) \right)$$

On average, when X and Y follow the unknown distribution of the datset

Loss measuring the "error" between prediction and label. Example: mean square error, loglikelihood ,…

Supervised learning reminders



$$f^* := \underset{f \in \text{All functions}}{\text{Argmin}} \left(\mathbb{E}(\text{ loss}(f(X), Y)) \right)$$

Not realistic to find minimizer among all possible functions!

Cannot compute! The true distribution is unknown.

- Instead, minimize in a class $\mathcal{F}$ of parametric functions
- $f^*_{\mathcal{F}} := \underset{f \in \mathcal{F}}{\text{Argmin}} \left(\mathbb{E}(\text{ loss}(f(X), Y))\right)$

- Approximation error:
  $\mathbb{E}(\text{loss}(f^*_{\mathcal{F}})) - \mathbb{E}(\text{loss}(f^*))$

Because f^* not in $\mathcal{F}$

- Instead, approximate by average on training set:
  $\mathbb{E}(\text{ loss}(f(X), Y)) \approx 1/n \sum_i \text{loss}(f(X_i), Y_i)$
- $f_n := \underset{f \in \mathcal{F}}{\text{Argmin}} \left(1/n \sum_i \text{loss}(f(X_i), Y_i) \right)$

- Estimation error:
  $\mathbb{E}(\text{ loss}(f_n)) - \mathbb{E}(\text{loss}(f^*_{\mathcal{F}}))$

Not enough data to identify $f^*_{\mathcal{F}}$

Model selection tradeoffs

$$f^* := \text{Argmin}\,(\mathbb{E}(\,\text{loss}(\,f(X), Y\,)\,)$$

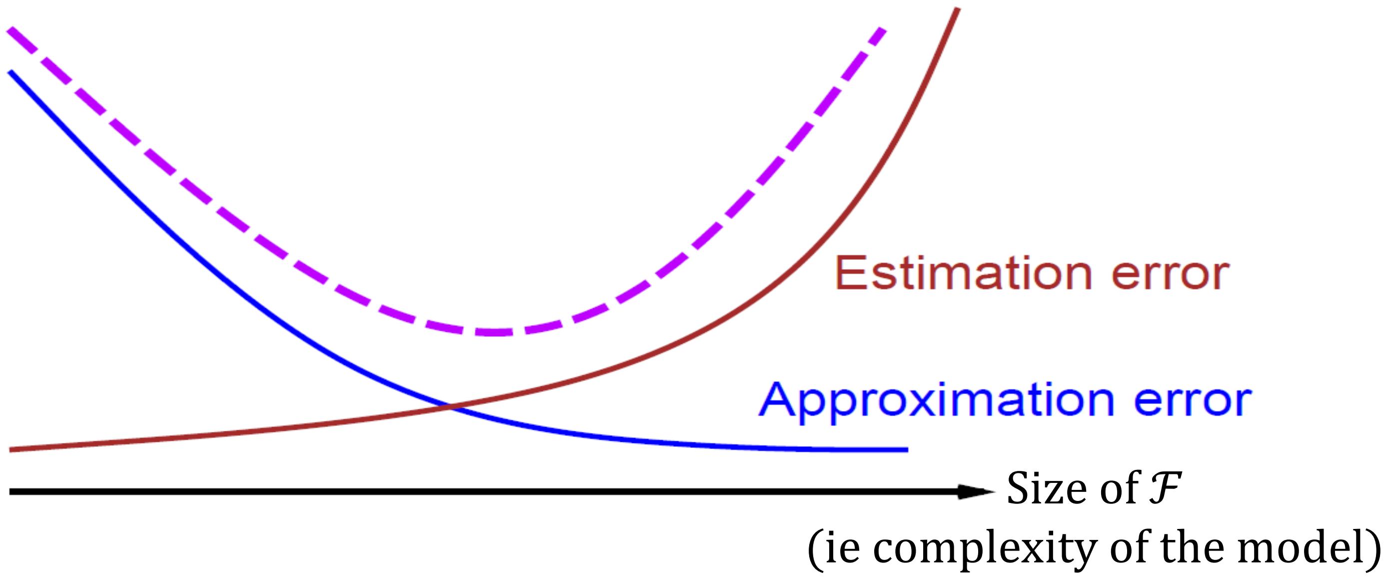
For a given dataset of size n →

$$f_n := \underset{f \in \mathcal{F}}{\text{Argmin}}\,(1/n\ \Sigma_i\ \text{loss}(\,f(X_i), Y_i)\,)$$

Error decomposition:

$$|\ \mathbb{E}(\text{loss}(\,f_n\,)) - \mathbb{E}(\text{loss}(\,f^*\,))\ | \ = |\ \mathbb{E}(\text{loss}(\,f^*_{\mathcal{F}}\,)) - \mathbb{E}(\text{loss}(f^*\,))\ |$$ Approximation error

$$+\ |\ \mathbb{E}(\text{loss}(f_n\,)) - \mathbb{E}(\text{loss}(\,f^*_{\mathcal{F}}\,))\ |$$ Estimation error



How complex a model can you afford with your data?

Learning with approximate optimization

Optimization problem.
Costly to solve accurately.

$$f_n := \underset{f \in \mathcal{F}}{\mathrm{Argmin}} \left(1/n \sum_i \mathrm{loss}(f(X_i), Y_i)\right)$$

- Instead: define stopping criteria ρ
- Let $\hat{f}_n$ the approximate solution returned by the optimizer.
- Error decomposition:

$$\begin{aligned} |\mathbb{E}(\mathrm{loss}(\hat{f}_n)) - \mathbb{E}(\mathrm{loss}(f^*))| &= |\mathbb{E}(\mathrm{loss}(f^*_{\mathcal{F}})) - \mathbb{E}(\mathrm{loss}(f^*))| && \text{Approximation error} \\ &+ |\mathbb{E}(\mathrm{loss}(f_n)) - \mathbb{E}(\mathrm{loss}(f^*_{\mathcal{F}}))| && \text{Estimation error} \\ &+ |\mathbb{E}(\mathrm{loss}(\hat{f}_n)) - \mathbb{E}(\mathrm{loss}(f_n))| && \text{Optimization error} \end{aligned}$$

- Choose $\mathcal{F}$, n, ρ to get small total error
- Subject to constraints: number of available samples, max compute time.

Small scale versus large scale

Small scale learning problem

- We have a small-scale learning problem when the active budget constraint is the number of examples n.

Large-scale learning problem

- We have a large-scale learning problem when the active budget constraint is the computing time T.

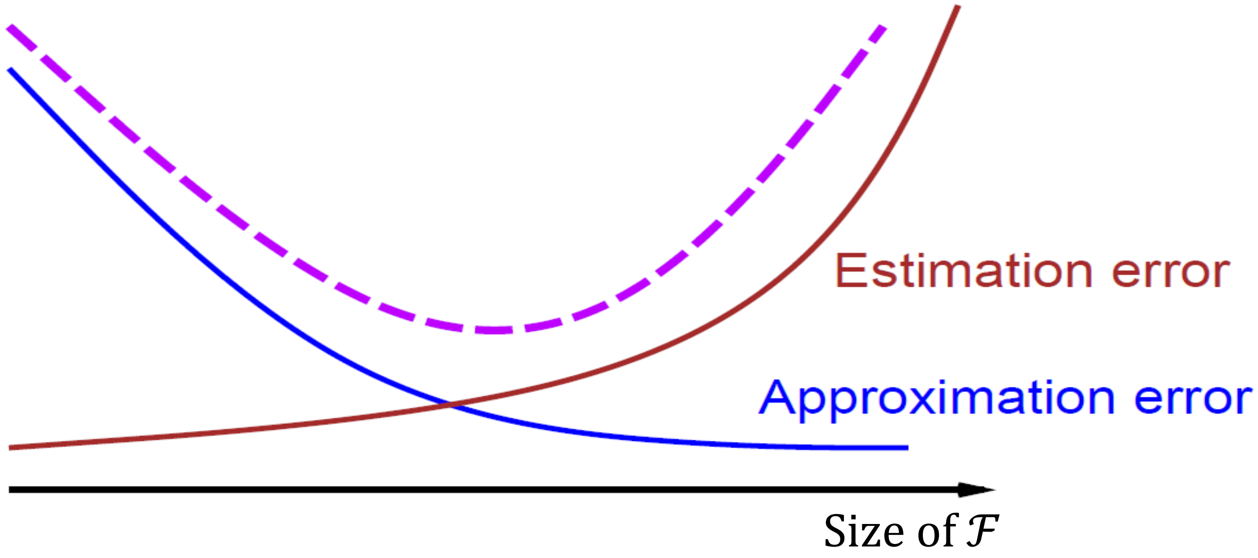
Small scale learning

Constrained by the number of samples

➔ Use all samples to reduce estimation error

Two degrees of freedom:

- Optimize as precisely as possible to avoid significative optimization error
- Select the size of $\mathcal{F}$ by crossvalidation



Large scale learning

Constrained by the training time / training ressources

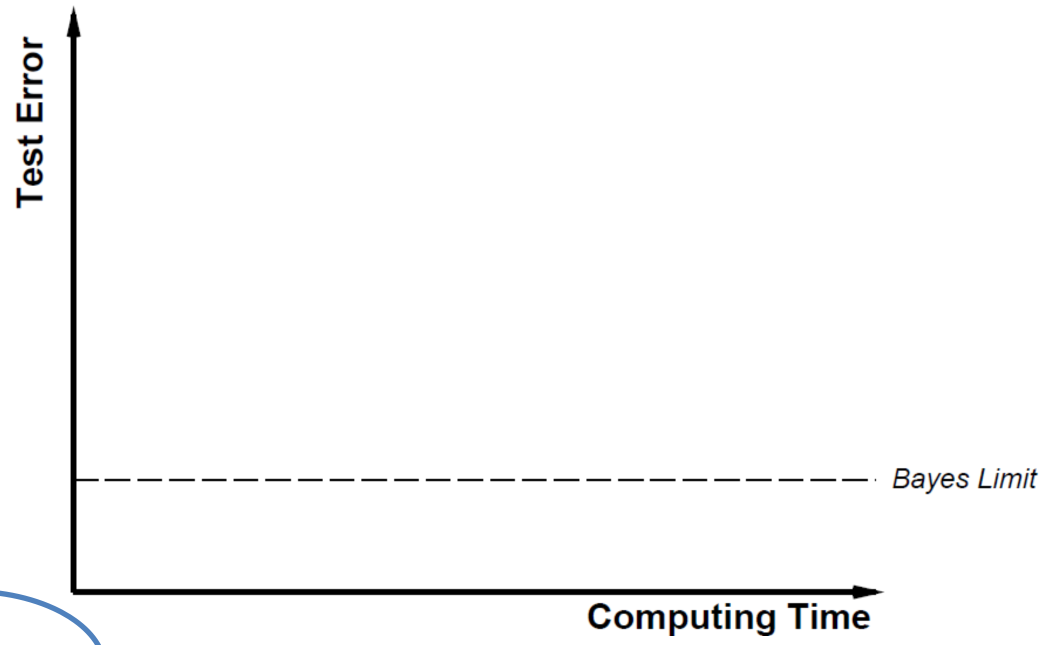
Example: OpenAI GPT-3 text model

- Training set: 45 TB text data, mostly crawled from internet.
- Training cost estimated to several M€

Computing time depends on n, $\mathcal{F}$ and ρ.

- Should you use more samples or spend more time optimizing on smaller sample set?
- Methods to reduce dataset size with small loss of precision may *improve* final performances!
- Best tradeof also depends on optimization algorithm.

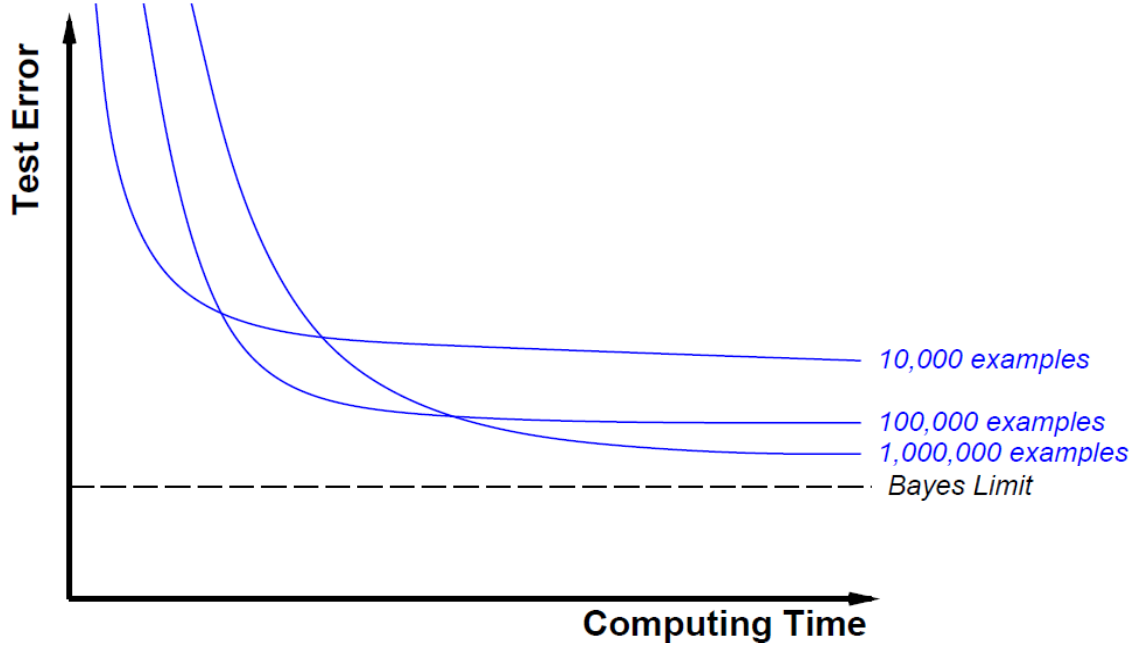
Test error versus computing time



Test error:

- $1/n_{test} \sum_{i \in TestSet} loss(\ \hat{f}_n(X_i), Y_i)$
- Unbiased estimator of $\mathbb{E}(loss(\hat{f}_n))$

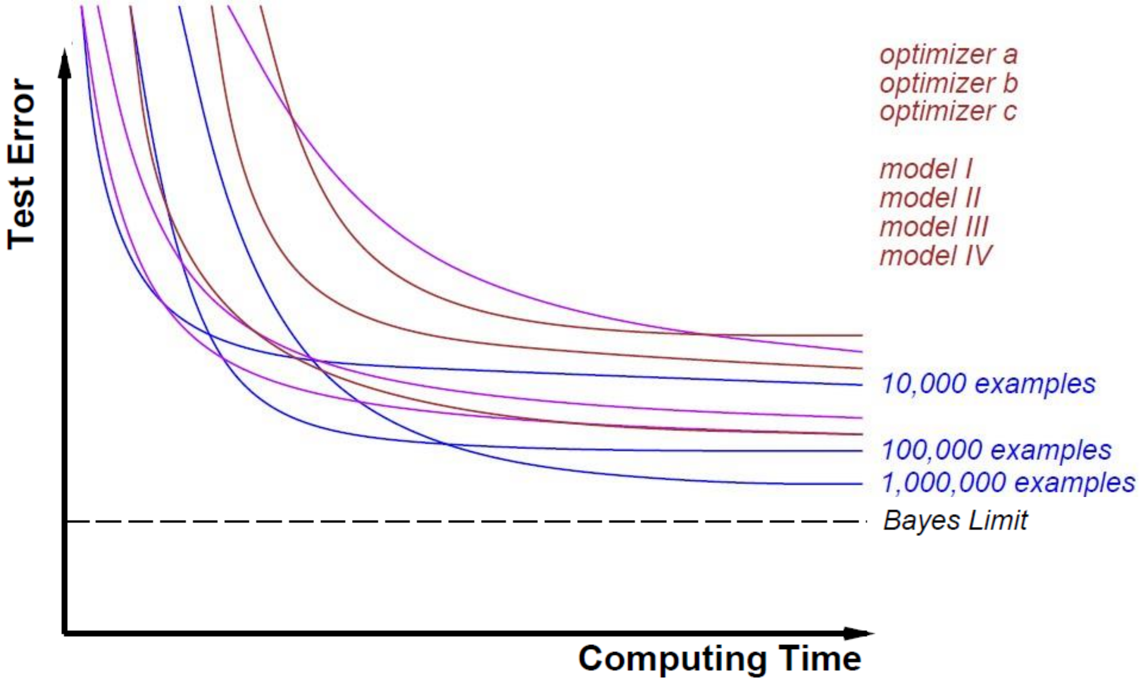
Test error versus computing time



Pushing optimization further, not changing n or $\mathcal{F}$

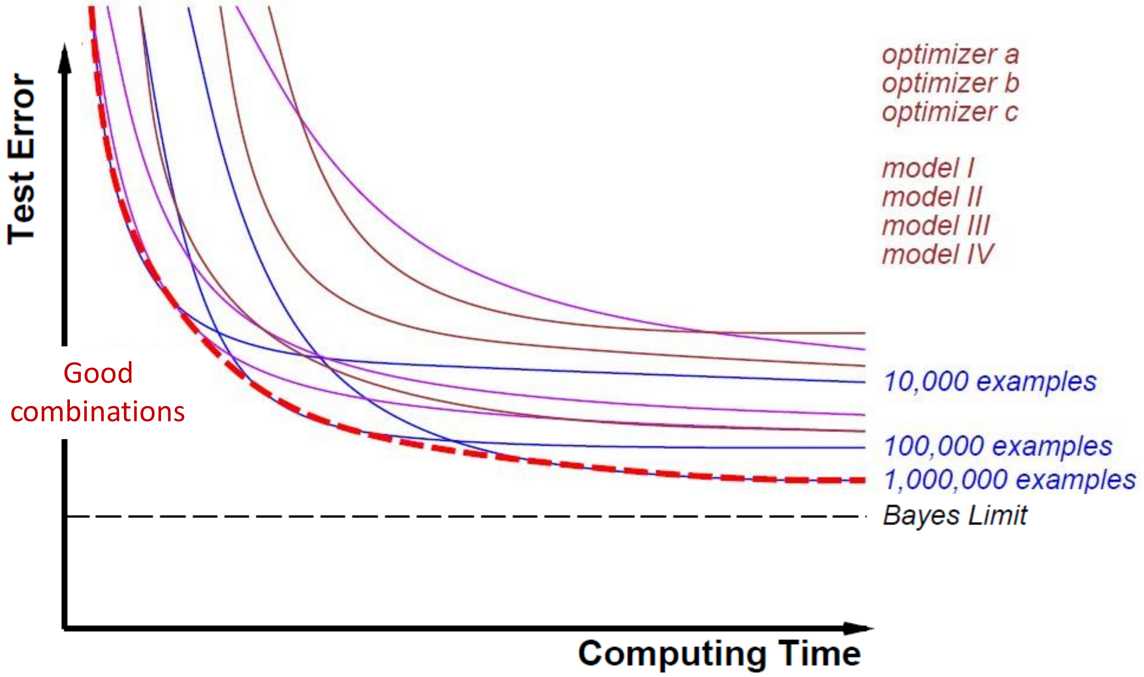
- Vary the number of examples

Test error versus computing time



- Vary the number of examples, the model, the algorithm

Test error versus computing time



- Optimal combination depends on training time budget.

The tradeoffs of large-scale learning

Small-scale learning ≠ large-scale learning

- Large-scale learning involves more complex tradeoffs
  that depends on the properties of the optimization algorithm.

Good optimization algorithm ≠ good learning algorithm

- Mediocre optimization algorithms (e.g., SGD)
  often outperform sophisticated optimization algorithms
  on large-scale learning problems.

Approximate optimization with large number of samples
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Precise optimization with few samples ?

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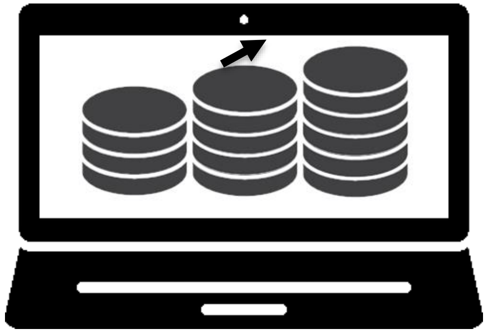
Tradeoffs

More Data ?

Labelling

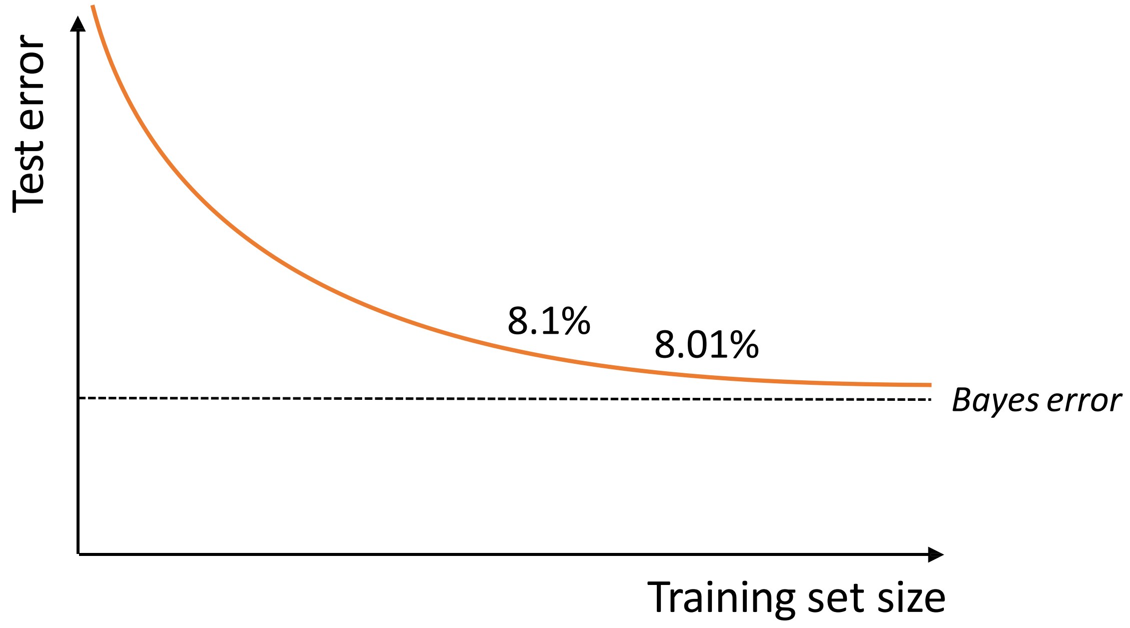


Scaling Tricks

More Data ?

Context

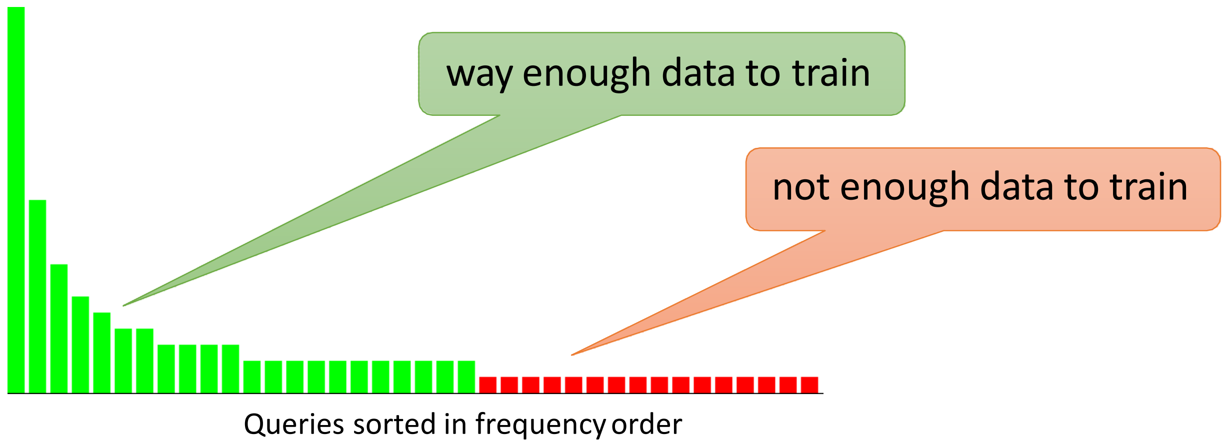
Dataset size: n
Training time: 12 hours (a bit too much but ok)
Loss: 8.01%



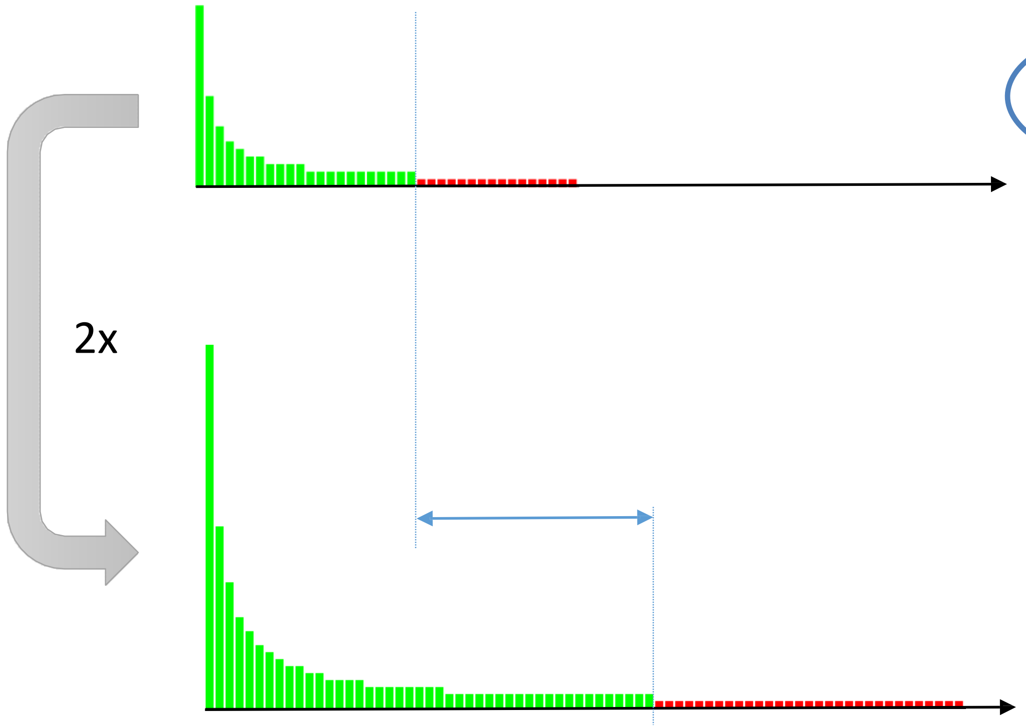
Question
Opportunity to use a dataset twice bigger.
What would you do ?

Zipf distributed data

Roughly half of the search queries are unique.



Doubling the size of the training set



Average error not much improved:
Most examples in the test set are from the head of the distribution, and already well predicted.

Proportion of distinct querries we learn to answer correctly increased a lot!

Value of big data

Accuracy improvements are subject to diminishing returns.

Breadth improvements are not subject to diminishing returns.

"How accurately do we recognize an object category?"

vs. "How many categories do we recognize well enough?"

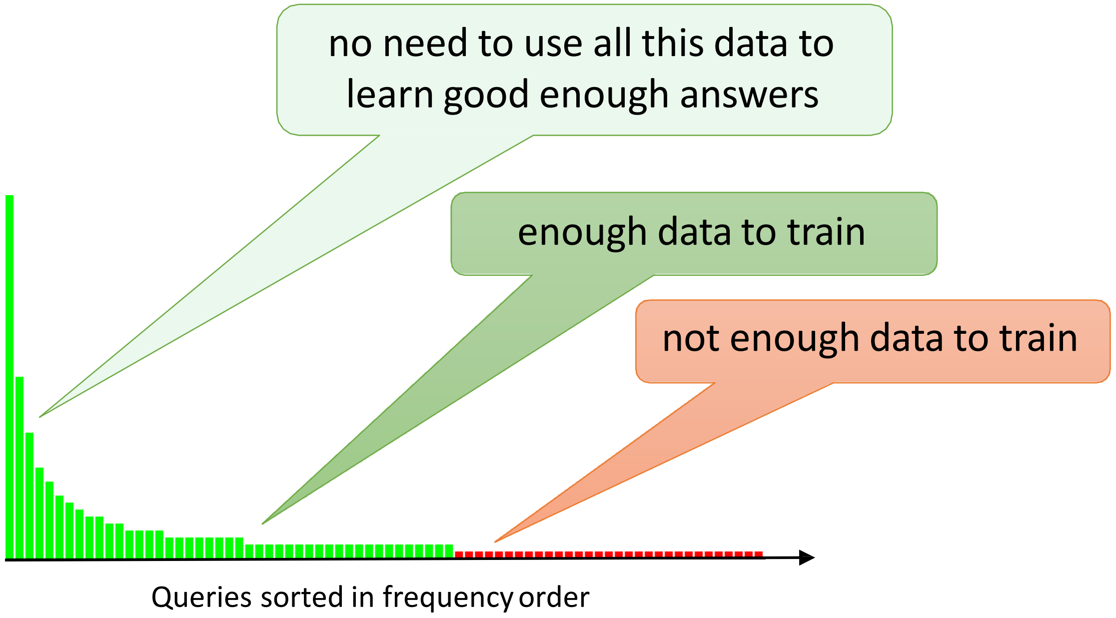
How does this help ? Average accuracy is all I care about !

Training time will double, I can't afford that…

Should I optimize a different criterion?

So what would you do ?

Harness Data, the scalable way



- No need to consider all examples of already known queries.
- Best is to focus on queries near the boundary of the known area.
- Curriculum learning and active learning come naturally in this context.
- Scalability gains across the board.

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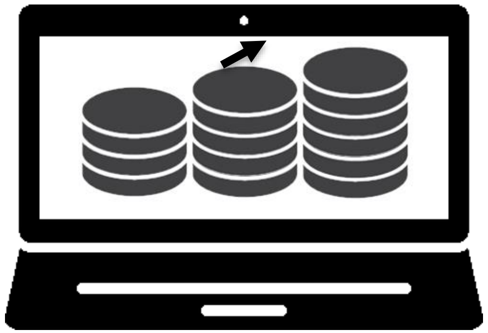


Scaling Tricks

Labelling

Data Augmentation

Cheap ways to get more labelled data !
Can you find some other ways ?

Dataset	Cheap Trick
Image	Translation, rotation, change scale, add noise…
Audio	noise, pitch…
Text	Replace word with synonym, syntax change, add/remove words, (shuffle)
Video	No need to label all images ; images from same sequence should have same label.

Transfer Learning

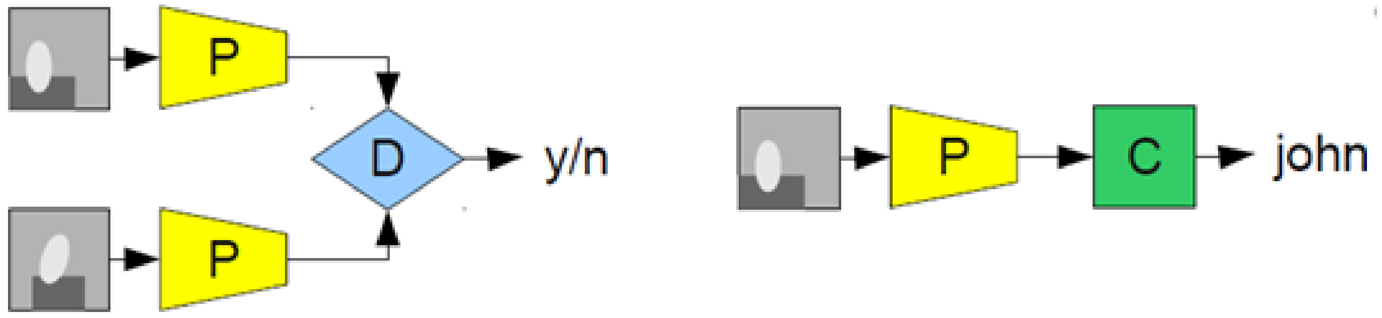
Idea

- Learn a representation on auxilliary task with cheap labels
- Finetune for your task

Or skip and use a pretrained model!

- Image processing
- Words embeddings

Example: face recognition



(Matt Miller, NECLA, 2006)

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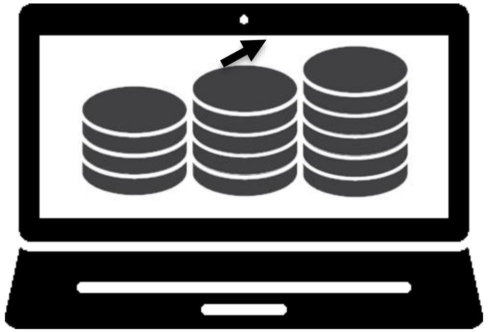

Scaling Tricks