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Introduction to ML strategy

Why ML Strategy?

- what's the best strategy to improve a certain DL system?

Motivating example

     

90%

Ideas:

- Collect more data ←
- Collect more diverse training set
- Train algorithm longer with gradient descent
- Try Adam instead of gradient descent
- Try bigger network
- Try smaller network

- Try dropout
- Add L_2 regularization
- Network architecture
  - Activation functions
  - # hidden units
  - …

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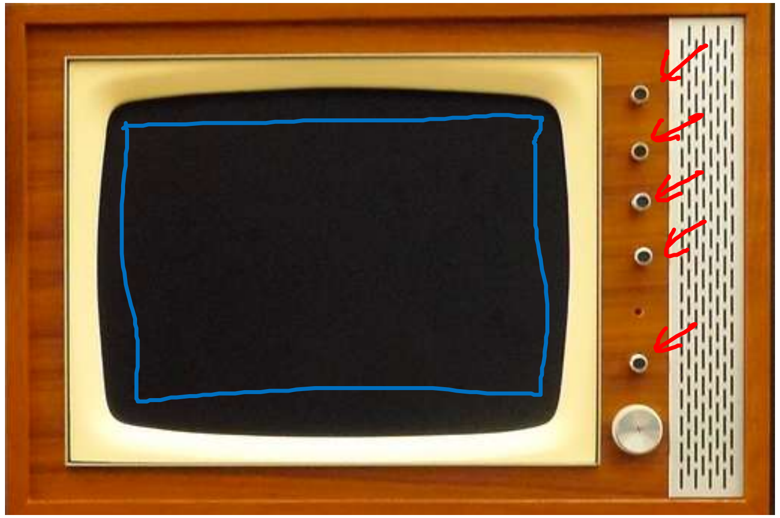
Introduction to ML strategy

Orthogonalization

- It's easier to change/tune the hyperparameters of the DL algorithm if their effects are independent from each other.

TV tuning example



0.1 ×

+ 0.3 ×

− 1.7 ×

+ 0.8 ×

+ ...

Orthogonalization

Car

→ Steering

→ Acceleration

Braking

→ 0.3 × angle − 0.8 speed

→ 2 × angle + 0.9 speed.

speed

angle

Chain of assumptions in ML

For ML applications we hope that

⑤ for ML we have orthogonal hyperparameters to try meeting each of the assumptions.

① basic fitting

→ Fit training set well on cost function

(≈ human-level performance)

bigger network
Adam
...

width

② generalization

DO NOT USE
early stopping

→ Fit dev set well on cost function

Regularization
Bigger train set

because it has effects on network size AND regularization and is therefore not orthogonal.

height

③ performance

→ Fit test set well on cost function

Bigger dev set
(existing dev set is not representative enough of the training set).

④ real-world performance

→ Performs well in real world

(Happy cat pic app users.)

Change dev set or cost function

?

- AT THE BEGINNING OF THE PROJECT ONE MUST IMMEDIATELY SET UP A DEV SET THAT REFLECTS THE REAL APPLICATION AND A PROPER EVALUATION METRICS.
- These should be reassessed periodically to compensate unforeseen side-effects.

Setting up your goal

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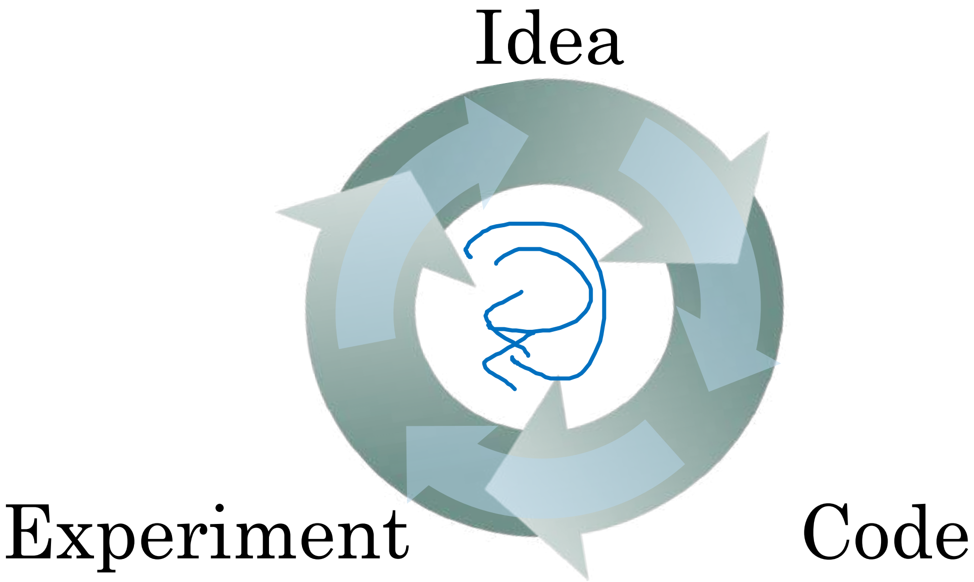
Single number evaluation metric

Using a single number evaluation metric



→ Of examples recognized as ~~cat~~ CATS, what % actually are cats? $\frac{TP}{TP+FP}$

→ what % of actual cats are correctly recognized $\frac{TP}{TP+FN}$

Classifier	Precision	Recall
A	95%	90%
B	98%	85%

F_1 score = "Average" of P and R.

($\frac{2}{\frac{1}{P}+\frac{1}{R}}$. "Harmonic mean")

Dev set + Single [real] number evaluation metric

Speed up iterating

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Another example

Algorithm	US	China	India	Other
A	3%	7%	5%	9%
B	5%	6%	5%	10%
C	2%	3%	4%	5%
D	5%	8%	7%	2%
E	4%	5%	2%	4%
F	7%	11%	8%	12%

AVERAGE

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Setting up your goal

Satisficing and optimizing metrics

Idea: one can have and combine different types of metrics. Some metrics need to be optimized (max/minimized), eg accuracy, others need only to be satisfied in a binary way (below/above a threshold), e.g. running time ≤ 100 ms.

Another cat classification example

optimizing Satisficing

Classifier	Accuracy	Running time
A	90%	80ms
B	92%	95ms
C	95%	1,500ms

cost = accuracy − 0.5 × running Time

maximize accuracy

subject to running Time ≤ 100 ms.

"Satisficing"

N metrics : 1 optimizing

N−1 satisficing

Wakewords / Trigger words

Alexa, OK Google,

Hey Siri, nihaobaidu

你好百度

accuracy.

#false positive

maximize accuracy.

s.t. ≤ 1 false positive

every 24 hours.

e.g. for Alexa we might want to maximize the recall, while ensuring the #FP ≤ 1 every 24 hours.

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Setting up your goal

Train/dev/test distributions

1- make sure that dev and test set come from the same distribution and represent well the real data the system will be used on.

Cat classification dev/test sets

development set, hold out cross validation set

Regions:

- US
- UK
- Other Europe
- South America
- India
- China
- Other Asia
- Australia

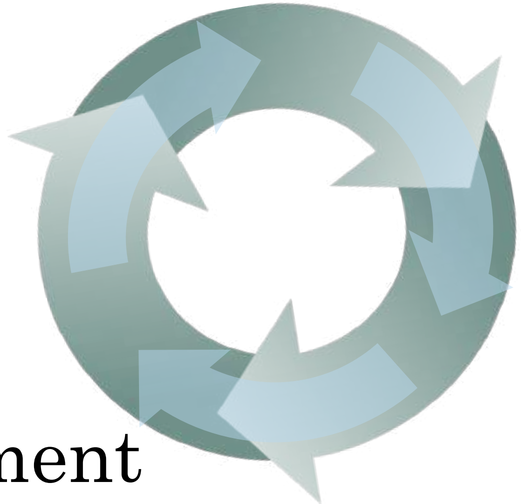
Dev

Test

Randomly shuffle into dev/test

dev set + metric

Idea



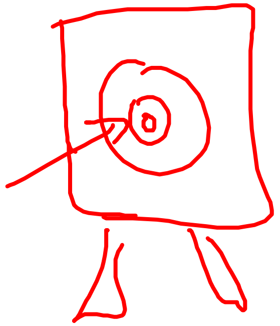
Experiment

Code

True story (details changed)

Optimizing on dev set on loan approvals for medium income zip codes

$x \longrightarrow y$ (repay loan?)



Tested on low income zip codes

~3 month

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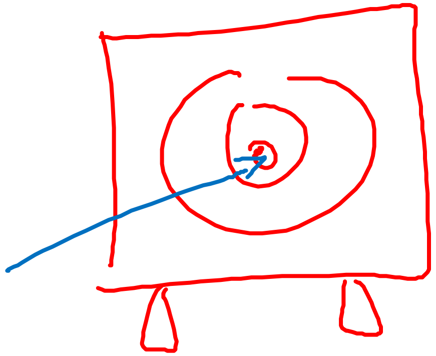
Guideline

Same distribution

Choose a dev set and test set to reflect data you expect to get in the future and consider important to do well on.

training



dev

metric

test

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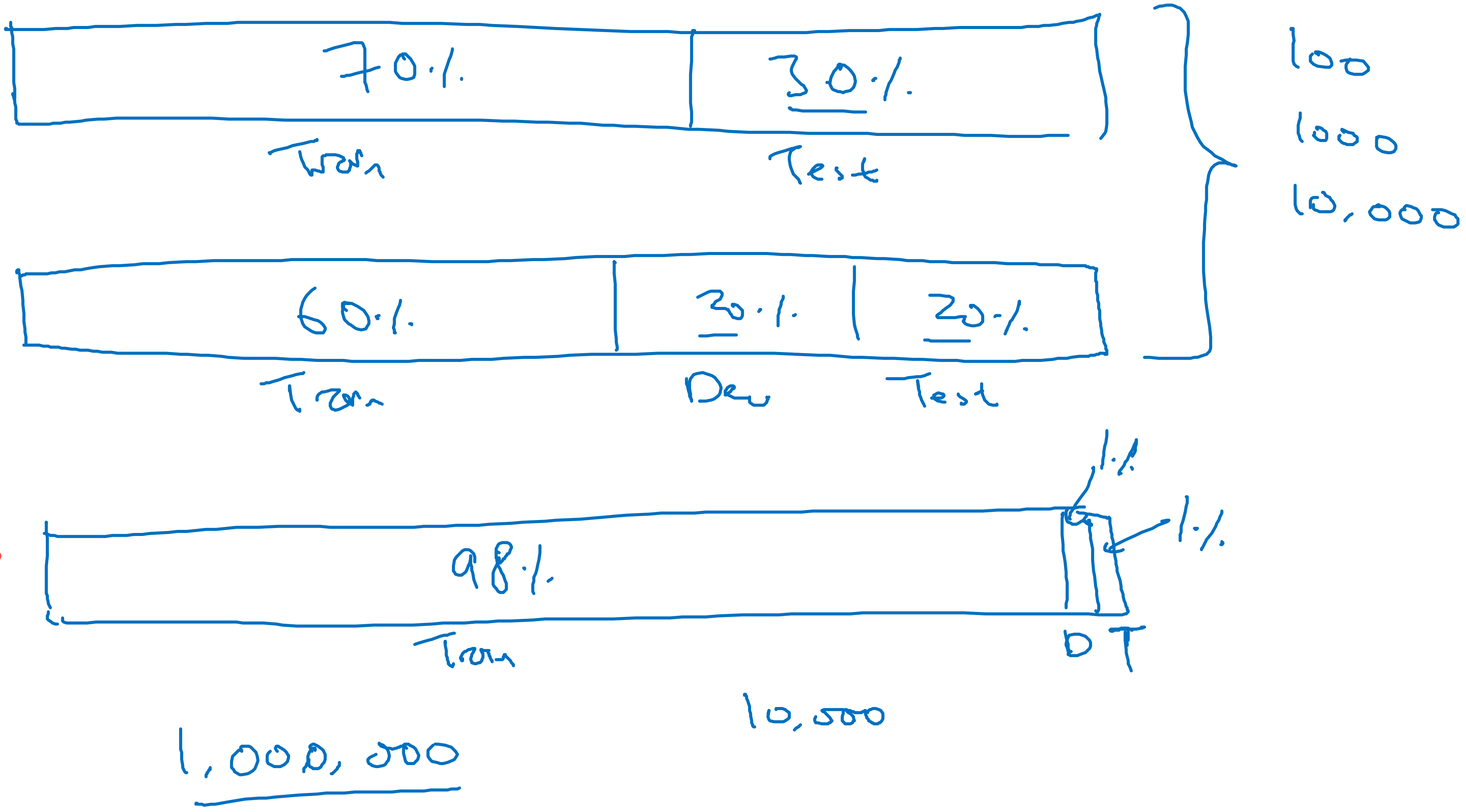
Setting up your goal

Size of dev and test sets

Old way of splitting data



In huge datasets (>1M samples) used for DL, one can split TR/DEV/TE 98% 1% 1%

Size of dev set

A B

Set your dev set to be big enough to detect differences in algorithm/models you're trying out.

100 : small

1%

1,000

10,000

100,000

A 97% → B 97.1%

0.1%

0.01%

0.001%

Online advertising

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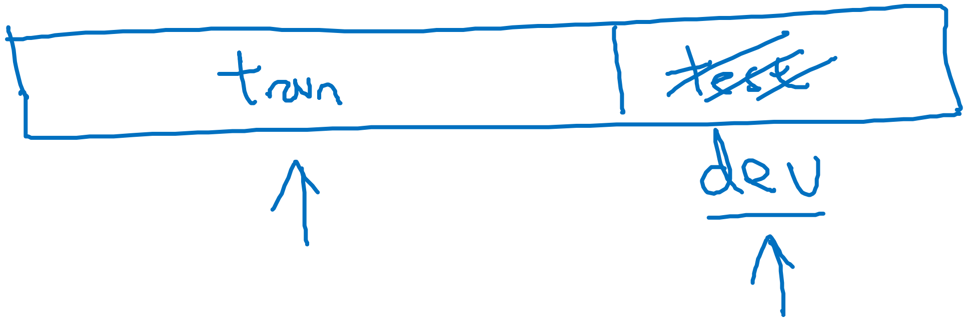
Size of test set

- Set your test set to be big enough to give high confidence in the overall performance of your system.

10,000

100,000

Train + Dev. No test set.



People sometimes do this but Ng does not recommend this.

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Setting up your goal

When to change dev/test sets and metrics

The performance metric and dev set must be corrected to catch unforeseen side effects.

Cat dataset examples

Metric + Dev : Prefer A
You/users : Prefer B.

→ Metric: classification error

Algorithm A: 3% error → pornographic

✓ Algorithm B: 5% error

$$\text{Error}: \frac{1}{\sum_i w^{(i)}} \cancel{\frac{1}{m_{dev}}} \sum_{i=1}^{m_{dev}} w^{(i)} \, \mathcal{I}\{ y_{pred}^{(i)} \neq y^{(i)} \}$$

predicted value (0/1)

$$\rightarrow \; w^{(i)} = \begin{cases} 1 & \text{if } x^{(i)} \text{ is non-porn} \\ 10 & \text{if } x^{(i)} \text{ is porn} \end{cases}$$

Orthogonalization for cat pictures: anti-porn

→ 1. So far we've only discussed how to define a metric to evaluate classifiers. ← Place target

→ 2. Worry separately about how to do well on this metric.

Aim/shoot at target

$$\rightarrow J = \frac{1}{\sum w^{(i)}} \sum_{i=1}^{m} w^{(i)} \mathcal{L}(\hat{y}^{(i)}, y^{(i)})$$

In case you wanna keep the metric (accuracy) you can decide to (orthogonally) modify the algorithm (loss in this case) so to counteract side effects.

↳ ? I don't fully get why one should change the loss but keep the old metric...

Another example

Algorithm A: 3% error

Algorithm B: 5% error

Dev/test

User images

If doing well on your metric + dev/test set does not correspond to doing well on your application, change your metric and/or dev/test set.

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Comparing to human-level performance

Why human-level performance?

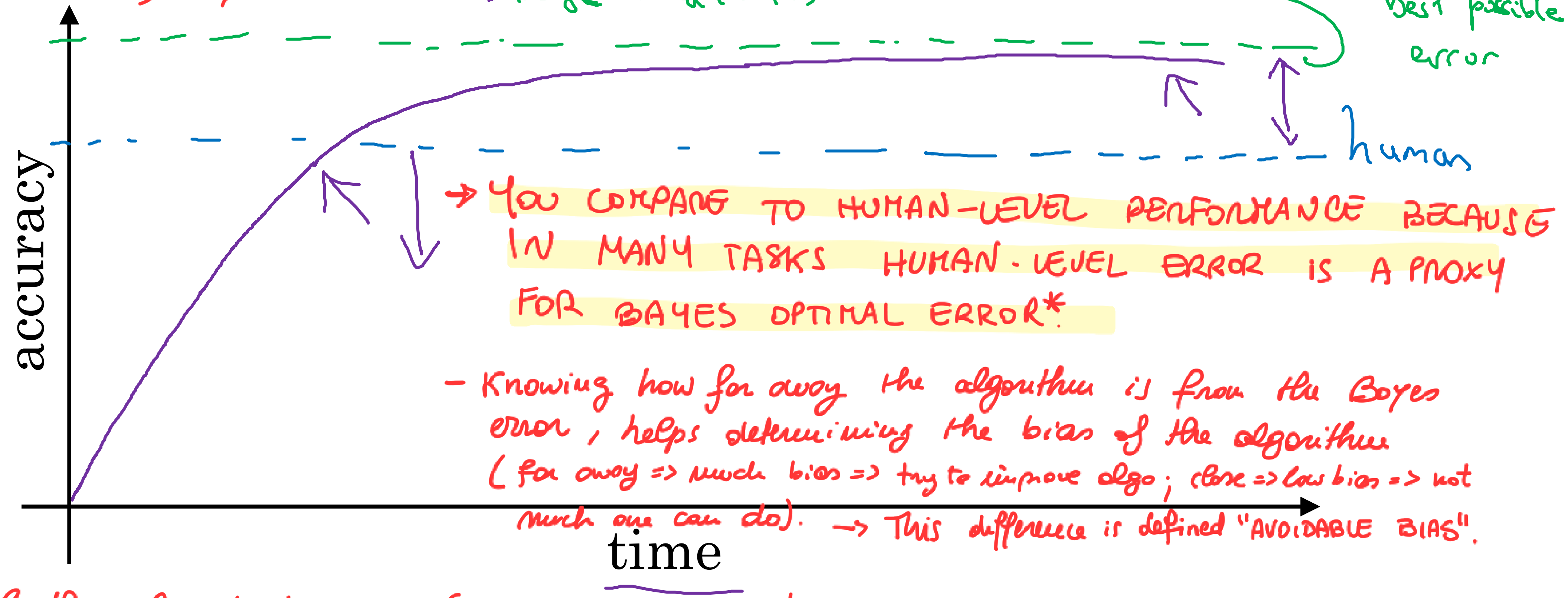
Comparing to human-level performance

- It is useful to know the human level performance on tasks where humans are not great, such as speech recognition with very noisy audio.

$X \rightarrow y$

→ audio → transcript

→ image → cat (0/1)



→ YOU COMPARE TO HUMAN-LEVEL PERFORMANCE BECAUSE IN MANY TASKS HUMAN-LEVEL ERROR IS A PROXY FOR BAYES OPTIMAL ERROR*.

- Knowing how far away the algorithm is from the Bayes error, helps determining the bias of the algorithm (far away => much bias => try to improve algo; close => low bias => not much one can do). → This difference is defined "AVOIDABLE BIAS".

- Moreover, until the algorithm's error (training error) is below human's error, the human can try to help the algorithm further (better labeling, identifying sources of noise); when the algorithm performs better than the human, this is not possible anymore.

*BAYES OPTIMAL ERROR: prediction error of the best function theoretically possible to solve the problem

Why compare to human-level performance

Humans are quite good at a lot of tasks. So long as ML is worse than humans, you can:

- Get labeled data from humans. (x, y)
- Gain insight from manual error analysis:
  Why did a person get this right?
- Better analysis of bias/variance. → explained later

- Until the algorithm's performance are worse than humans, the human can do a lot to improve the algorithm's performance (labeling, identifying sources of imprecision in the algorithm, deciding if the bias of the algorithm is too high).

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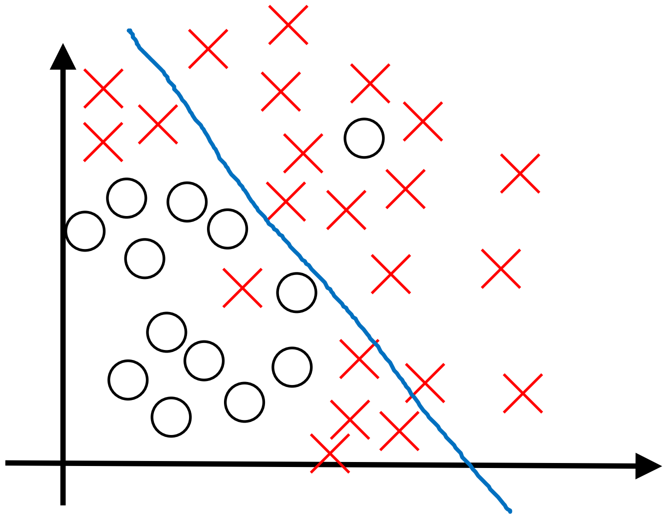
Comparing to human-level performance

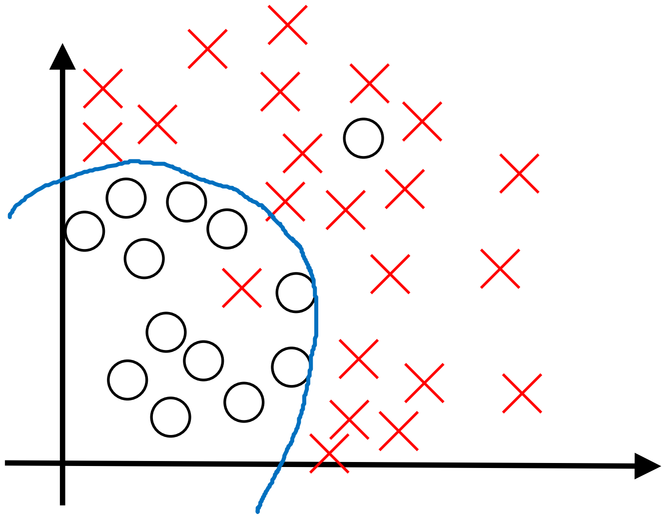
Avoidable bias

Bias and Variance

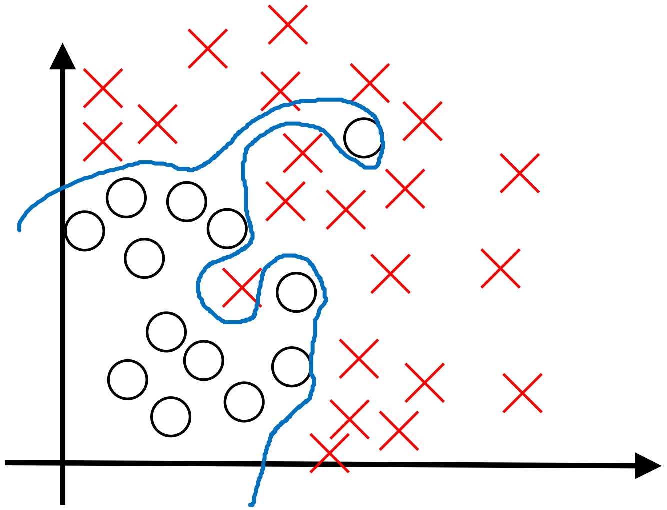


high bias

underfitting



"just right"



high variance

overfitting.

Bias and Variance

Cat classification

Human-level ≈ 0% ....

Training set error:

Dev set error:

high variance   high bias   high bias   low bias
                                    high variance   low variance

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Cat classification example

AVOIDABLE BIAS: difference between training error and (approximation of) Bayes error. This bias can likely be modified acting on the algorithm.

Humans (≈ Bayes)	1%	7.5%
Training error	8%	8 %
Dev error	10%	10 %

7% 2% 0.5% 2% 2%

Variance

Avoidable bias

Variance

Focus on bias

Focus on variance

Human-level error as a proxy for Bayes error.

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Comparing to human-level performance

Understanding human-level performance

Human-level error as a proxy for Bayes error

Medical image classification example:

Suppose:

(a) Typical human ………………… 3 % error

(b) Typical doctor ……………………. 1 % error

(c) Experienced doctor …………….. 0.7 % error

(d) Team of experienced doctors .. 0.5 % error

Baye error $\leq$ 0.5%

What is "human-level" error?

Error analysis example

Human (proxy for Bayes error)	1% 0.7% 0.5%	1% 0.7% 0.5%	0.7% 0.5% 1%
Avoidable bias	4% 4.5%	0% 0.5%	0.2% 0.0%
Training error	5%	1%	$\boxed{0.7\%}$
Variance	1%	4%	0.1%
Dev error	6%	5%	0.8%
	Bias	Variance	

Summary of bias/variance with human-level performance

0%

"Bias"

Human-level error

(proxy for Bayes error)

"Avoidable bias"

Training error

"Variance"

Dev error

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Comparing to human-level performance

Surpassing human-level performance

Surpassing human-level performance

Team of humans	0.5%	0.5%
One human	~~1%~~	1%
Training error	0.6%	0.3%
Dev error	0.8%	0.4%

0.1

0.2

0.1%

0.2%

0.3%

What is avoidable bias?

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Problems where ML significantly surpasses human-level performance

→ - Online advertising

→ - Product recommendations

→ - Logistics (predicting transit time)

→ - Loan approvals

Structured data

Not natural perception

Lots of data

- Speech recognition
- Some image recognition
- Medical
  - ECG, Skin cancer, ...

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Comparing to human-level performance

Improving your model performance

The two fundamental assumptions of supervised learning

1. You can fit the training set pretty well.

   Reduce

   ~ Avoidable bias

2. The training set performance generalizes pretty well to the dev/test set.

   Reduce

   ~ Variance

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Reducing (avoidable) bias and variance

Human-level = Proxy for Bayes error

Avoidable bias

Training error

Variance

Dev error

Train bigger model

Train longer/better optimization algorithms

- momentum, RMSprop, Adam
- step size, #epochs

NN architecture/hyperparameters search

RNN
CNN

- activation functions, #layers, # hidden units

More data

Regularization

- L_2, dropout, data augmentation

NN architecture/hyperparameters search