Objective of this course is to get the machine learnig system working

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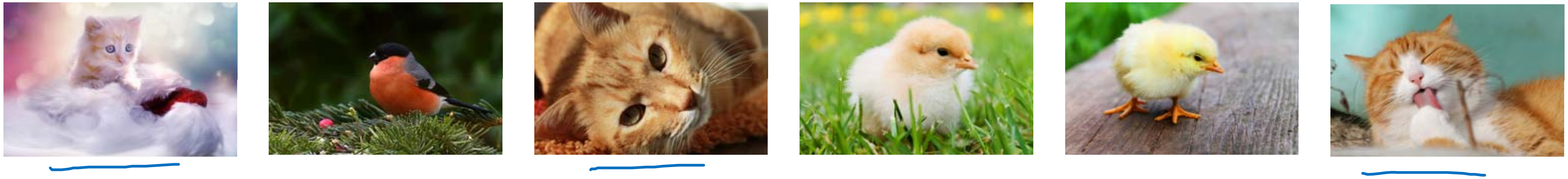
Introduction to ML strategy

Why ML Strategy?

What is machine learning strategy. Thats start with a motivating example.

Motivating example



90%

say u get 90% accurency but this is not good enogh for you application
what u can do is:

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
  - …

There are a lot of ideas of what to change so u have to be carefull in what u choose to change,
it could take months to make these changes and then realize they are usles

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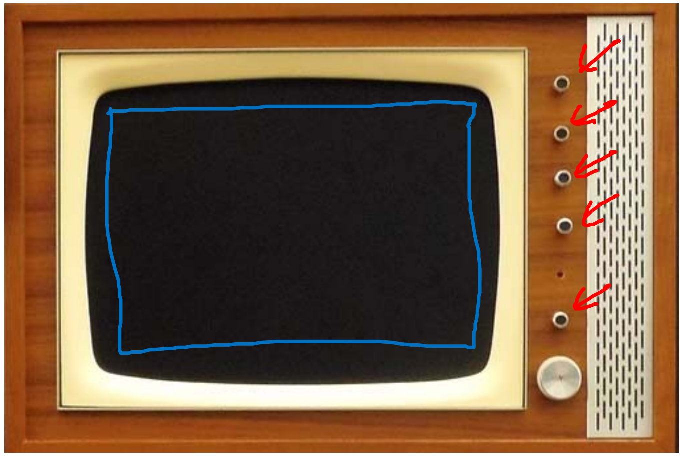
Introduction to ML strategy

Orthogonalization

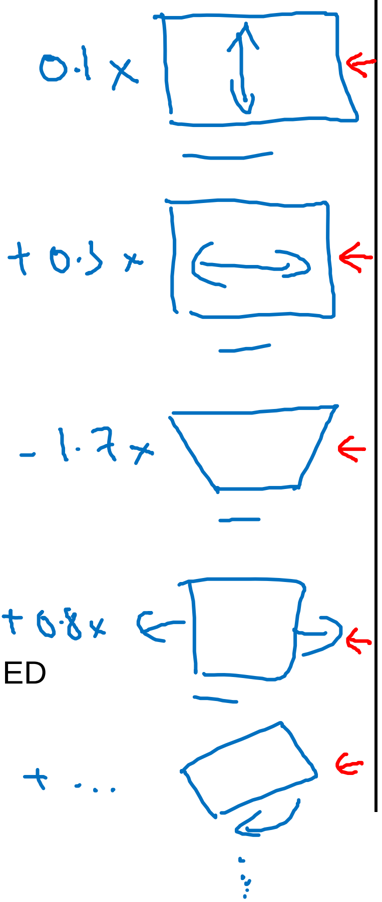
what to tune to achive one effect, this is a process we call orthogonalization.

TV tuning example



Orthogonalization

IT MEANS THAT EACH KNOB WAS DESIGNED
TO DO ONE THINK



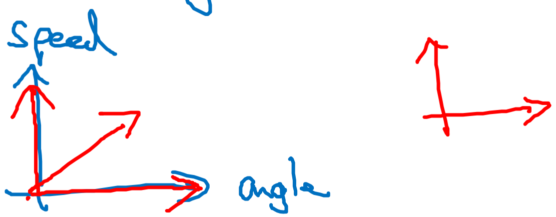
Car

→ Steering

→ Acceleration
Braking

→ 0.3 x angle − 0.8 speed

→ 2 x angle + 0.9 speed.



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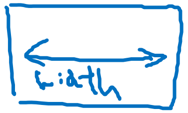
Chain of assumptions in ML

→ Fit training set well on cost function

(≈ human-level performance)

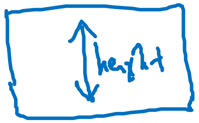
bigger network
Adam
...

early stopping



→ Fit dev set well on cost function

Regularization
Bigger train set



→ Fit test set well on cost function

Bigger dev set

→ Performs well in real world

(Happy cat pic app users.)

Change dev set or cost function

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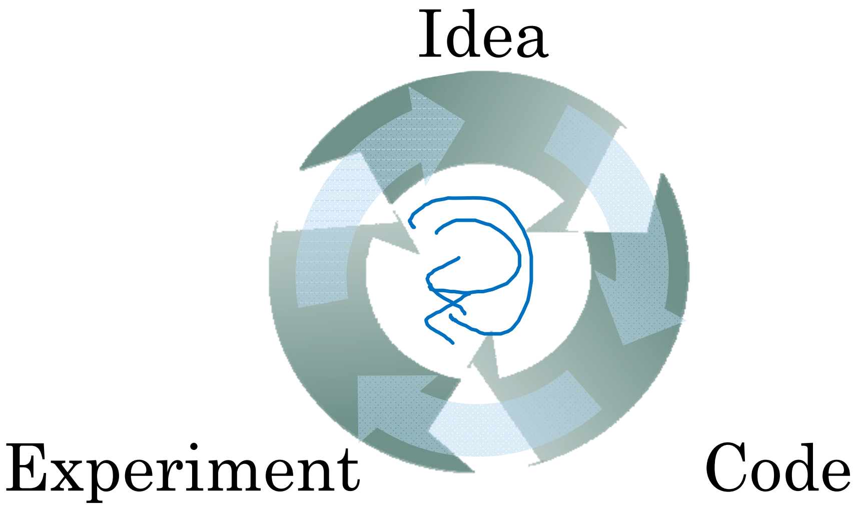
Setting up
your goal

Single number evaluation metric

Using a single number evaluation metric



→ Of examples recognized as cat, what % actually are cats?

Of examples recognised as cats what % actually are cats?

→ what % of actual cats are correctly recognized

what % of actual cats are correctly recognized

Classifier	Precision	Recall	F1 Score
A	95%	90%	92.4%
B	98%	85%	91.0%

F_1 score = "Average" of P and R.

its an avg of precision and recall

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

Dev set + Single number evaluation metric

real

Speed up iterating

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Another example

Algorithm	US	China	India	Other	Average
A	3%	7%	5%	9%	6%
B	5%	6%	5%	10%	6.5%
C	2%	3%	4%	5%	3.5%
D	5%	8%	7%	2%	5.25%
E	4%	5%	2%	4%	3.75%
F	7%	11%	8%	12%	9.5%

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Setting up your goal

Satisficing and optimizing metrics

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 runnig Time ≤ 100 ms.

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.

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Setting up your goal

Train/dev/test distributions

Cat classification dev/test sets

development set, hold out cross validation set

Regions:

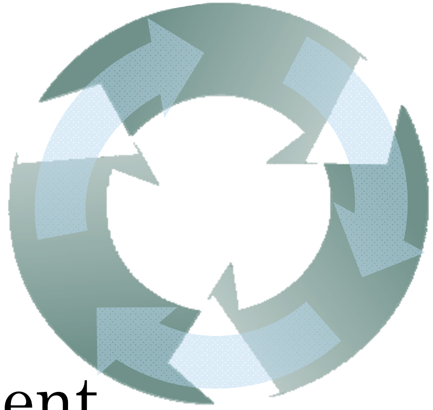
- US
- UK
- Other Europe
- South America
- India
- China
- Other Asia
- Australia

Dev

Test

Randomly shuffle into dev/test

dev set + metric



Idea

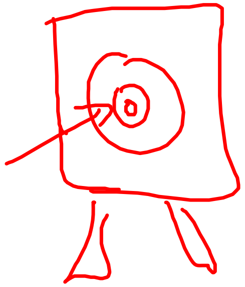
Code

Experiment

True story (details changed)

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

$X \rightarrow y$ (repay loan?)



Tested on low income zip codes

~3 month

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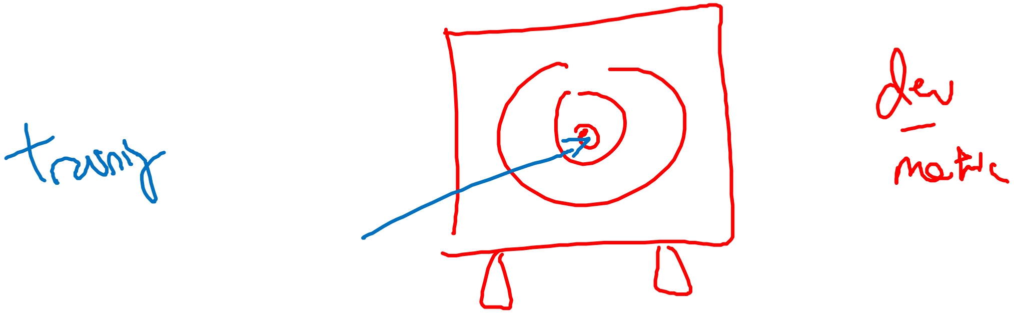
Guideline

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.



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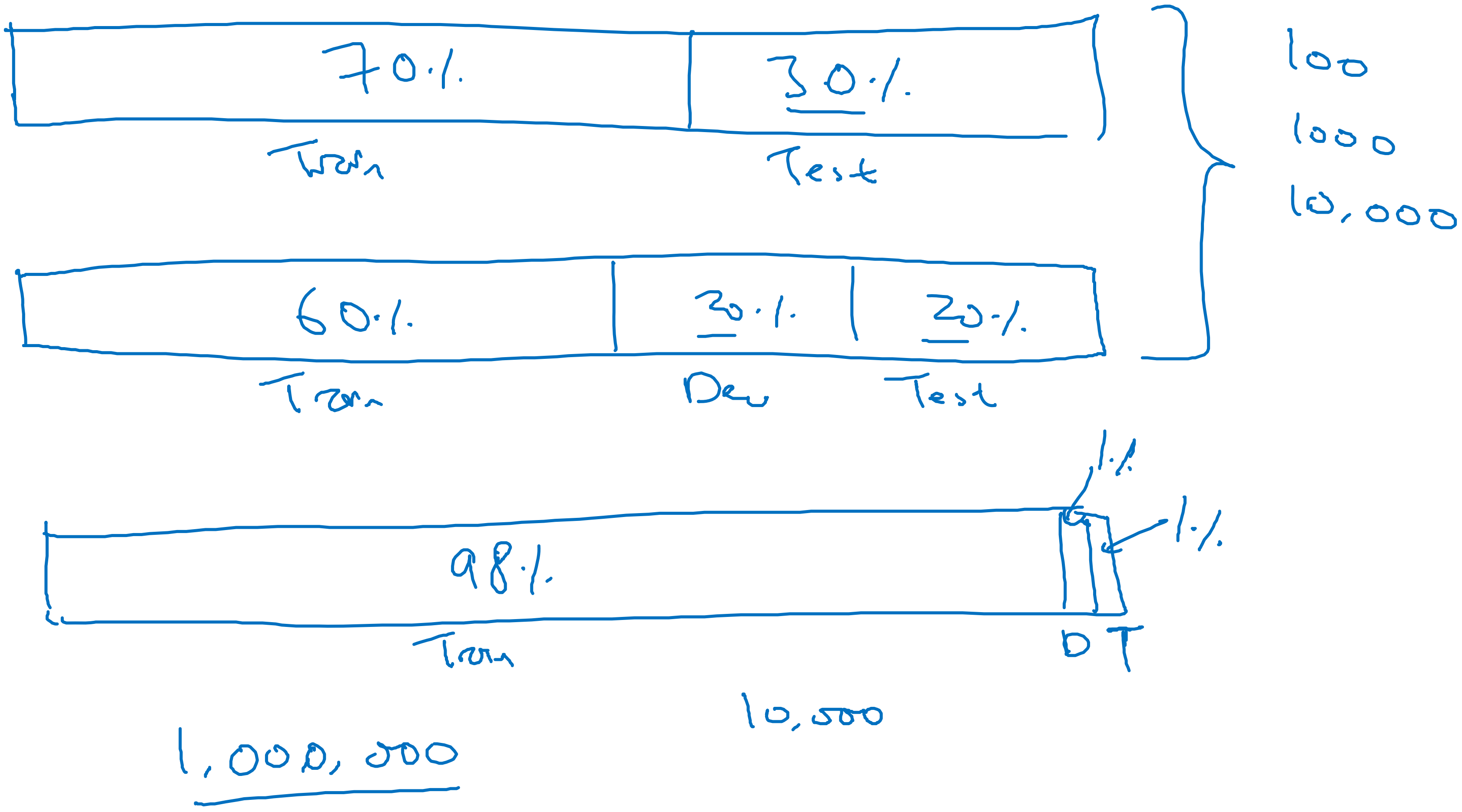
Setting up your goal

Size of dev and test sets

Old way of splitting data



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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

$\overset{A}{97\%} \longrightarrow \overset{B}{97.1\%}$

0.1%

0.01%

0.001%

Online advertising

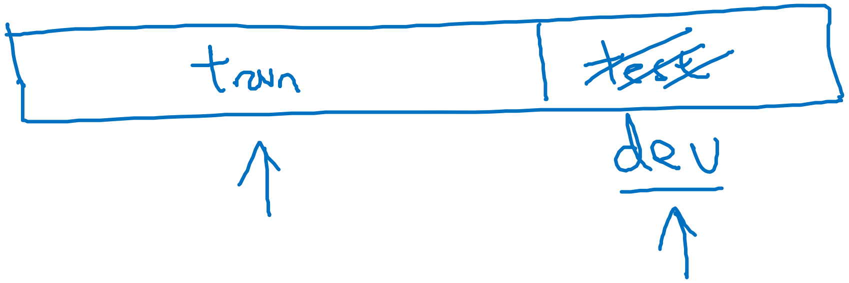
Size of test set

- 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.



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Setting up your goal

When to change dev/test sets and metrics

Cat dataset examples

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

Metric: classification error

Algorithm A: 3% error → pornographic

✓ Algorithm B: 5% error

$$\text{Error: } \frac{1}{\sum_i w^{(i)}} \cancel{\frac{1}{m_{dev}}} \sum_{i=1}^{m_{dev}} w^{(i)} \, \mathcal{I}\{ \underbrace{y_{pred}^{(i)} \neq y^{(i)}}_{\text{predicted value } (0/1)} \}$$

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

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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

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

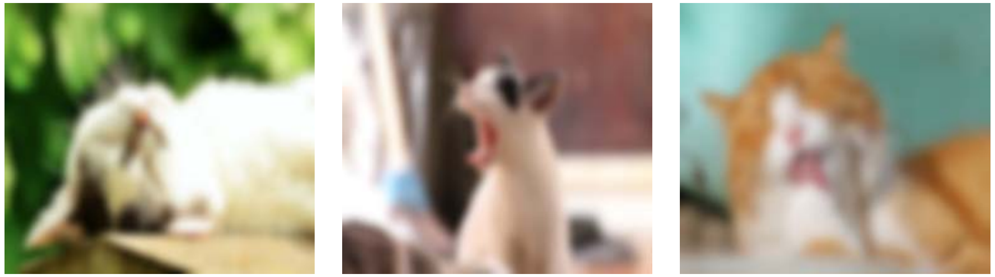
Another example

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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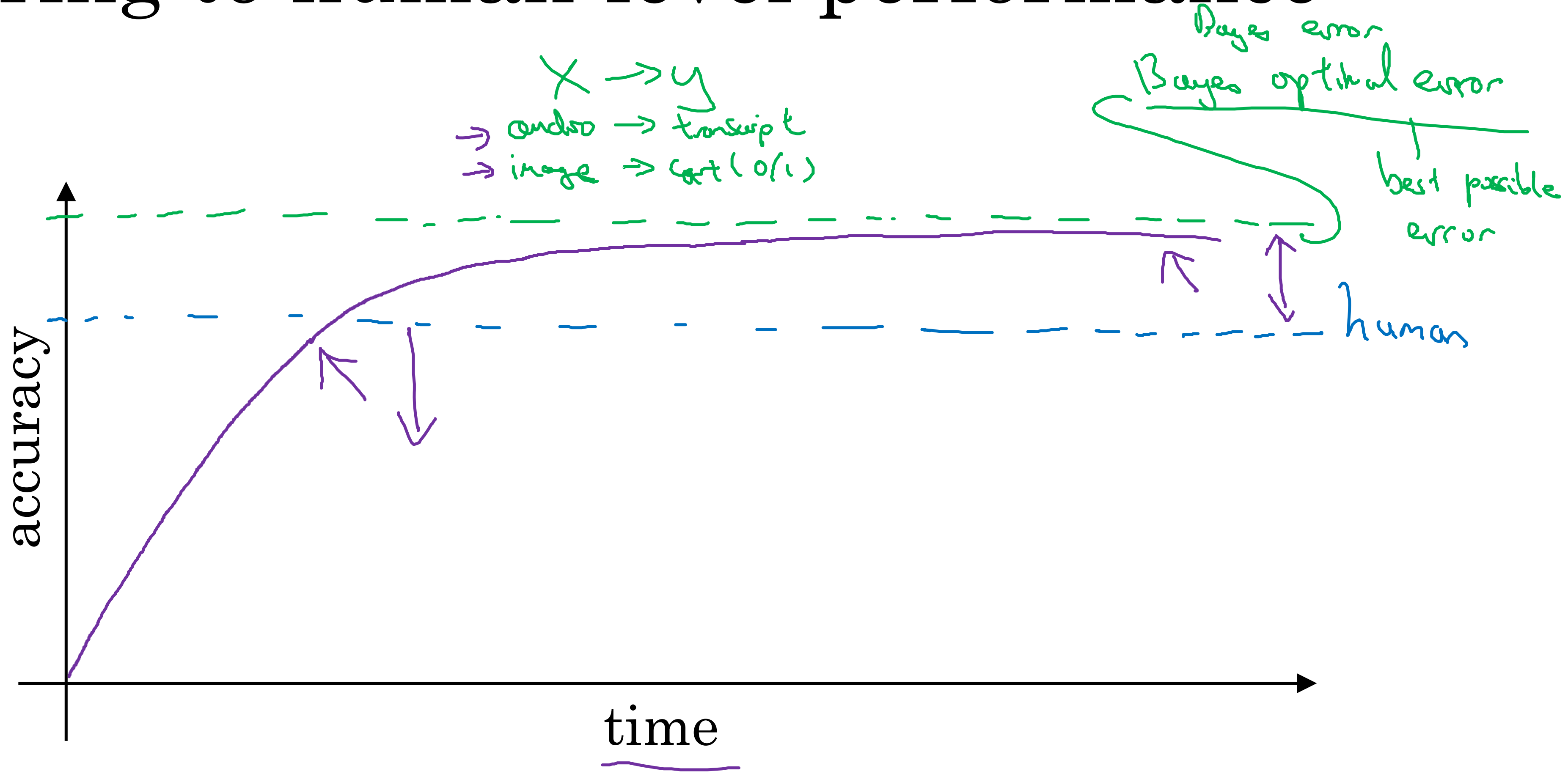
Comparing to human-level performance

Why human-level performance?

Comparing to human-level performance


X → y

→ audio → transcript

→ image → cat (0/1)

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.

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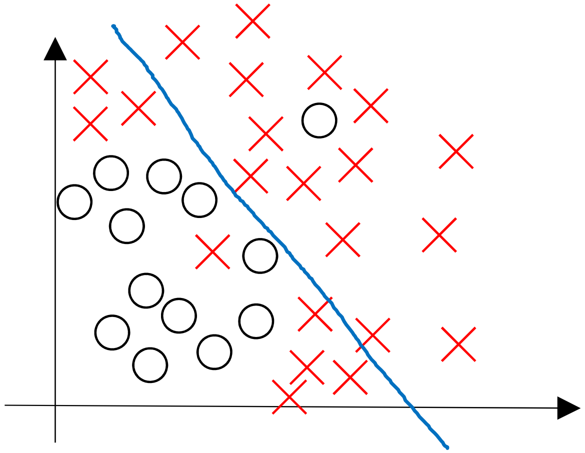
Comparing to human-level performance

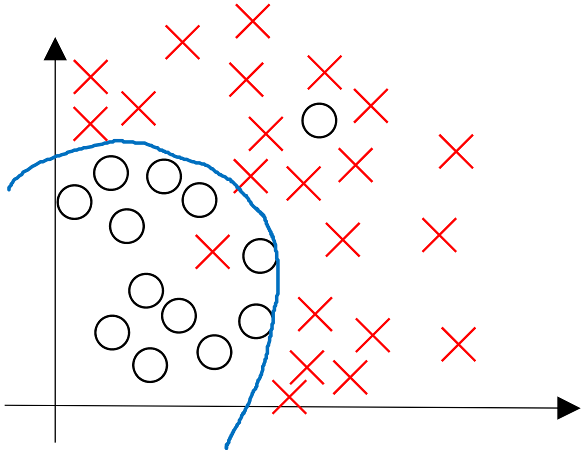
Avoidable bias

Bias and Variance

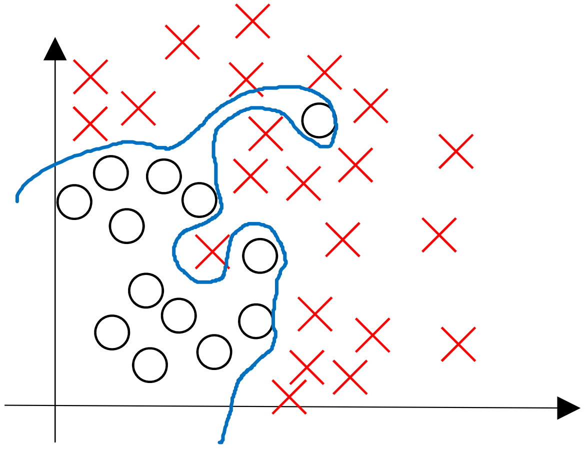


high bias

underfitting



"just right"



high variance

overfitting.

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Bias and Variance

Cat classification

Human-level ≈ 0% ....

Training set error:

Dev set error:

high variance

high bias

high bias
high variance

low bias
low variance

Cat classification example

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

7%

2%

2%

0.5%

Avoidable bias

variance

2%

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

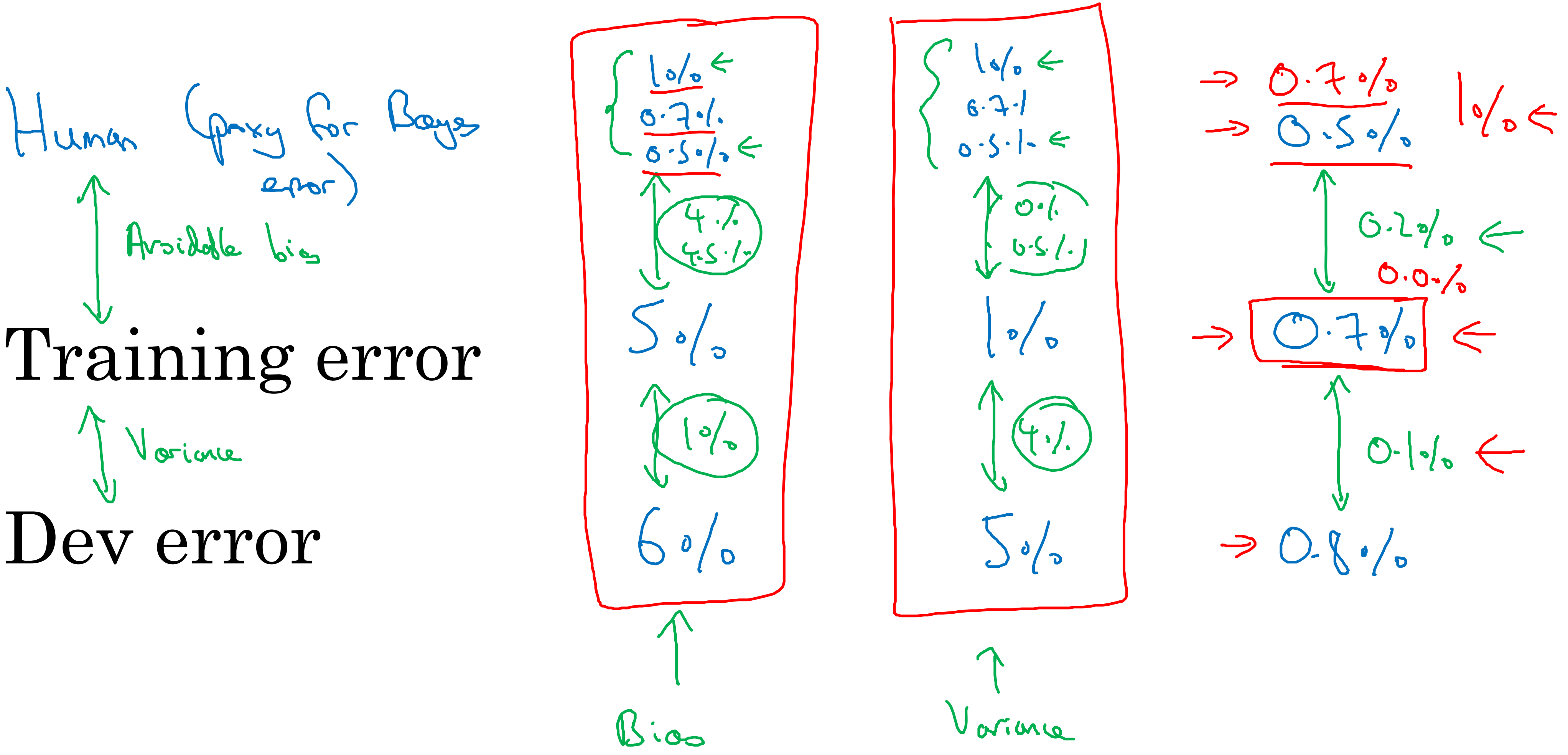
(c) Experienced doctor …………… 0.7 % error

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

Baye error ≤ 0.5%

What is "human-level" error?

Error analysis example



Training error

Dev error

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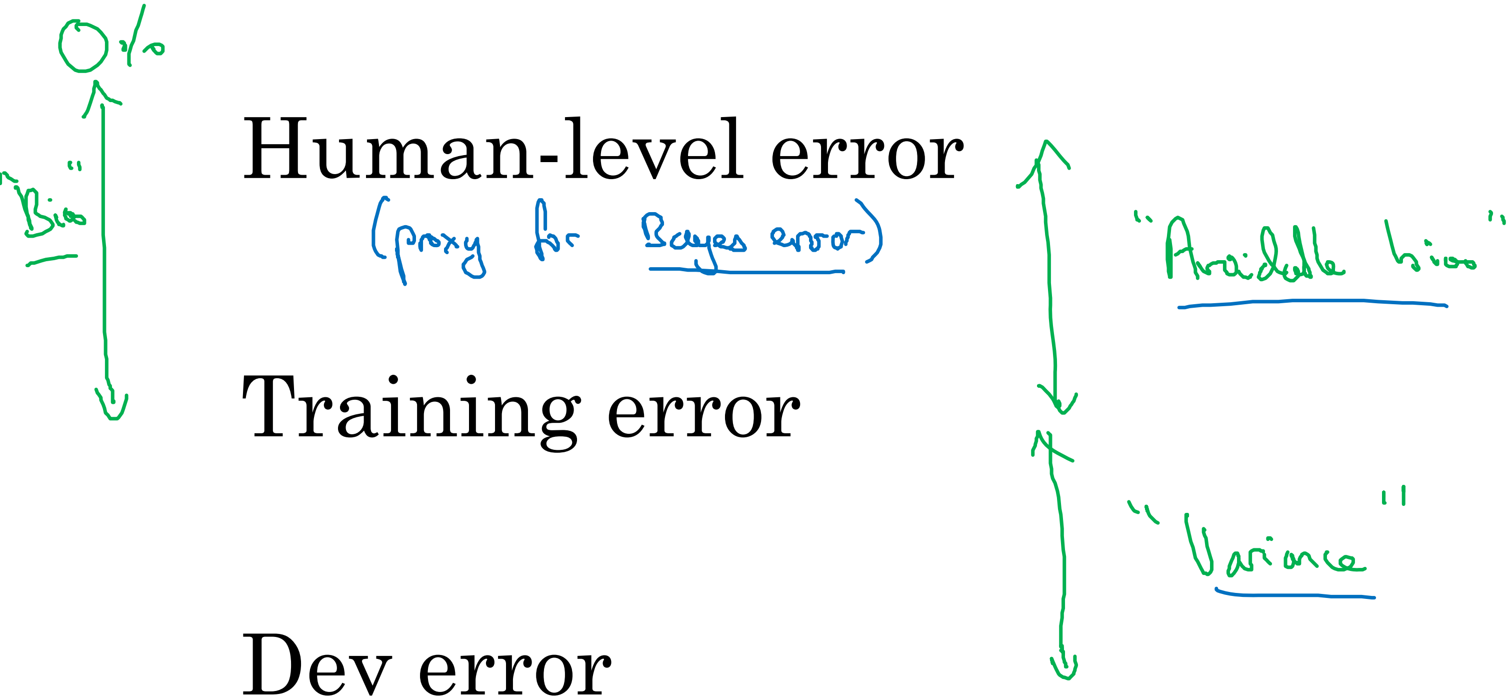
Summary of bias/variance with human-level performance



Human-level error

Training error

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?

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.

   $\sim$ Avoidable bias

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

   $\sim$ Variance

Reducing (avoidable) bias and variance

Human-level

Avoidable bias

Training error

Variance

Dev error

Train bigger model

Train longer/better optimization algorithms

- momentum, RMSprop, Adam

NN architecture/hyperparameters search

RNN
CNN

More data

Regularization

- L_2, dropout, data augmentation

NN architecture/hyperparameters search

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