deeplearning.ai

Introduction to ML strategy

Why ML Strategy?

Motivating example

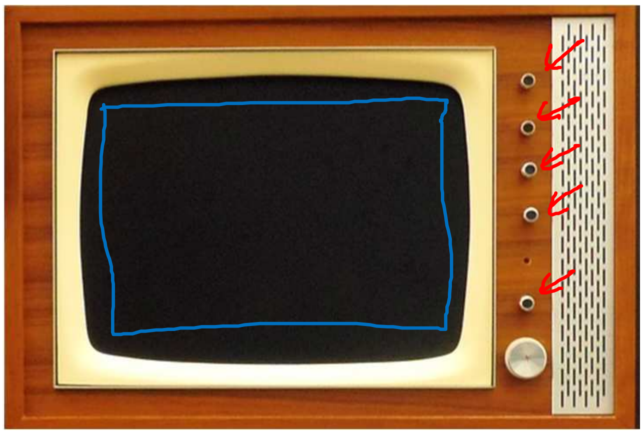
     

90%

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
    - …

TV tuning example



Orthogonalization

$0.1 \times$

$+ 0.3 \times$

$- 1.7 \times$

$+ 0.8 \times$

$+ \ldots$

Car

→ Steering

→ Acceleration

Braking

→ $0.3 \times$ angle $-$ 0.8 speed

→ $2 \times$ angle $+$ 0.9 speed.

speed

angle

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Chain of assumptions in ML

→ Fit training set well on cost function

(≈ human-level performance)

bigger network
Adam
...

width

→ Fit dev set well on cost function

early stopping

Regularization
Bigger train set

height

→ 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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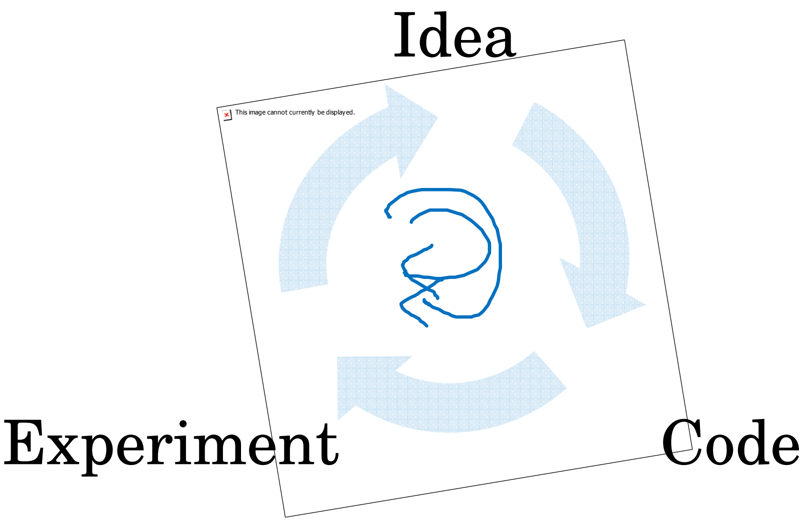
Using a single number evaluation metric



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

→ what % of actual cats are correctly recognized

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

F_1 score = "Average" of P and R.

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

Dev set + Single number evaluation metric

real Speed up iterating

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%

Cat classification dev/test sets

development set, hold out cross validation set

Regions:

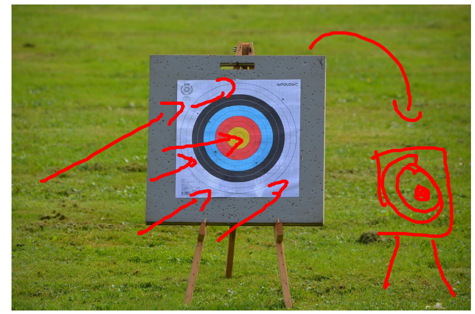
- US
- UK
- Other Europe
- South America

Dev

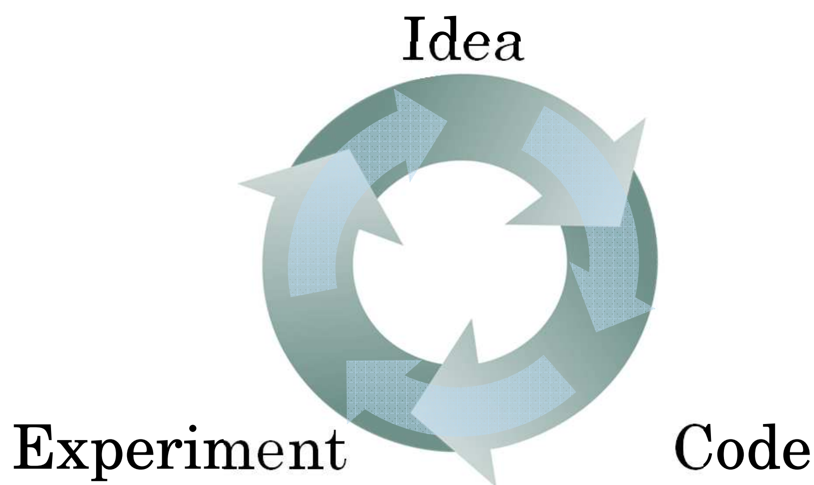
- India
- China
- Other Asia
- Australia

Test

Randomly shuffle into dev/test



dev set + metric



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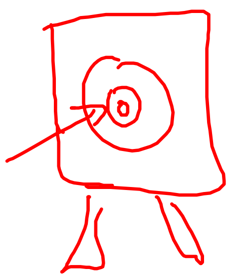
True story (details changed)

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

$x \rightarrow y$ (repay loan?)



Tested on low income zip codes

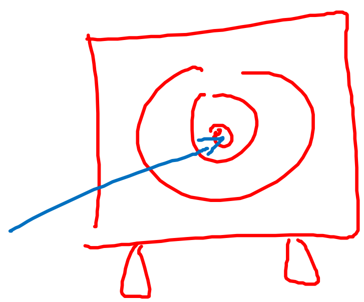
~ 3 month

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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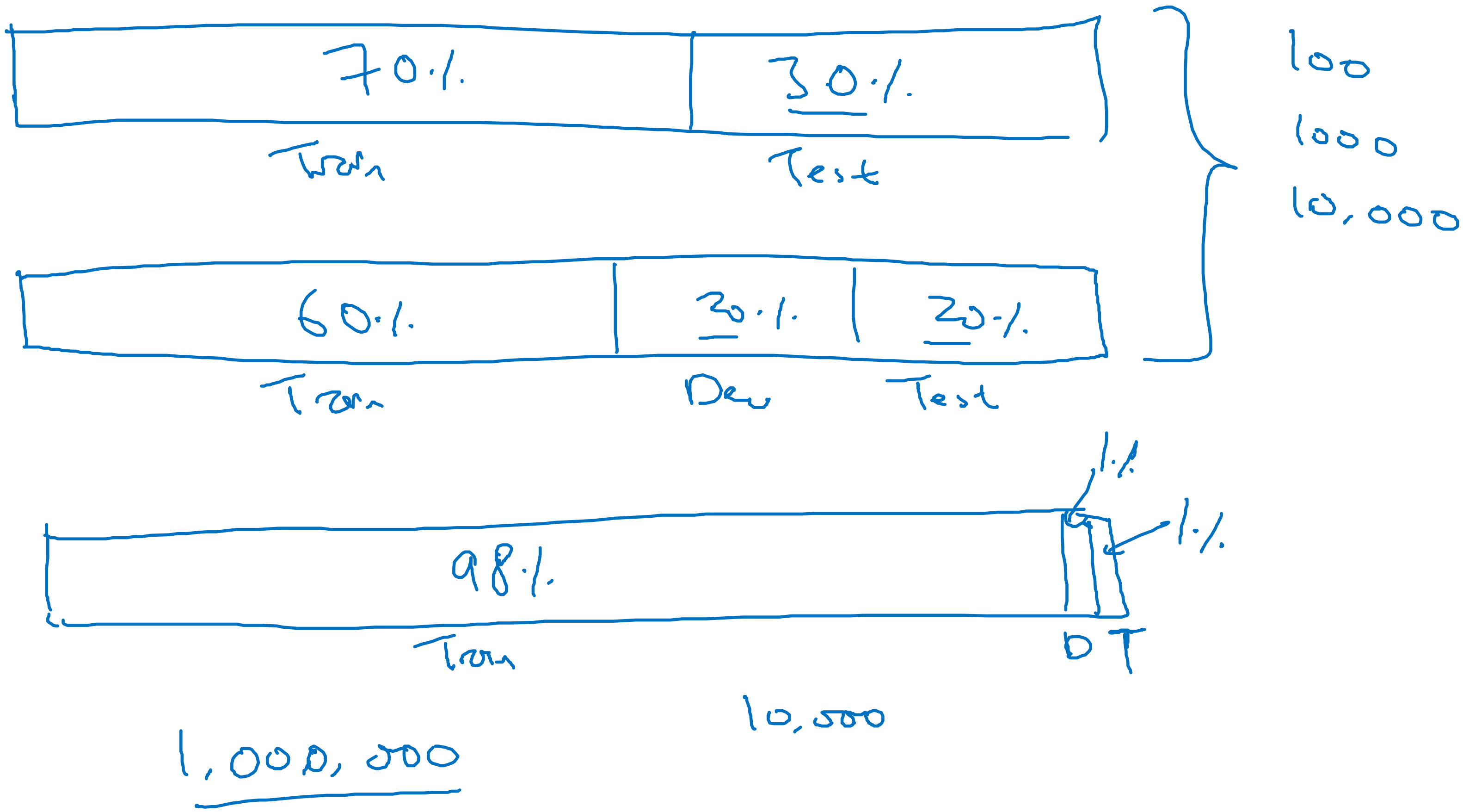
Old way of splitting data



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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%

A: 97% → B: 97.1%

0.1%

1,000

10,000

100,000

0.01%

0.001%

Online advertising

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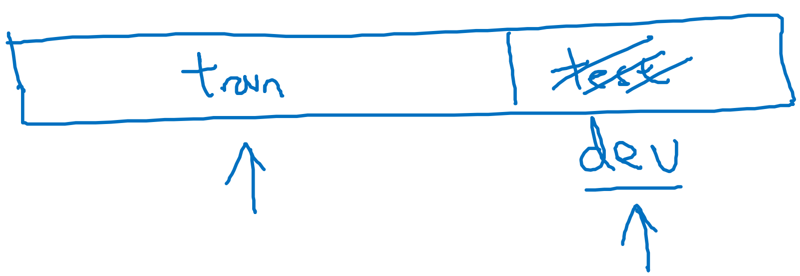
Size of test set

- 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.



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Cat dataset examples

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

- Metric: classification error

  Algorithm A: 3% error → pornographic

  Algorithm B: 5% error

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

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

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

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

Another example

Algorithm A: 3% error

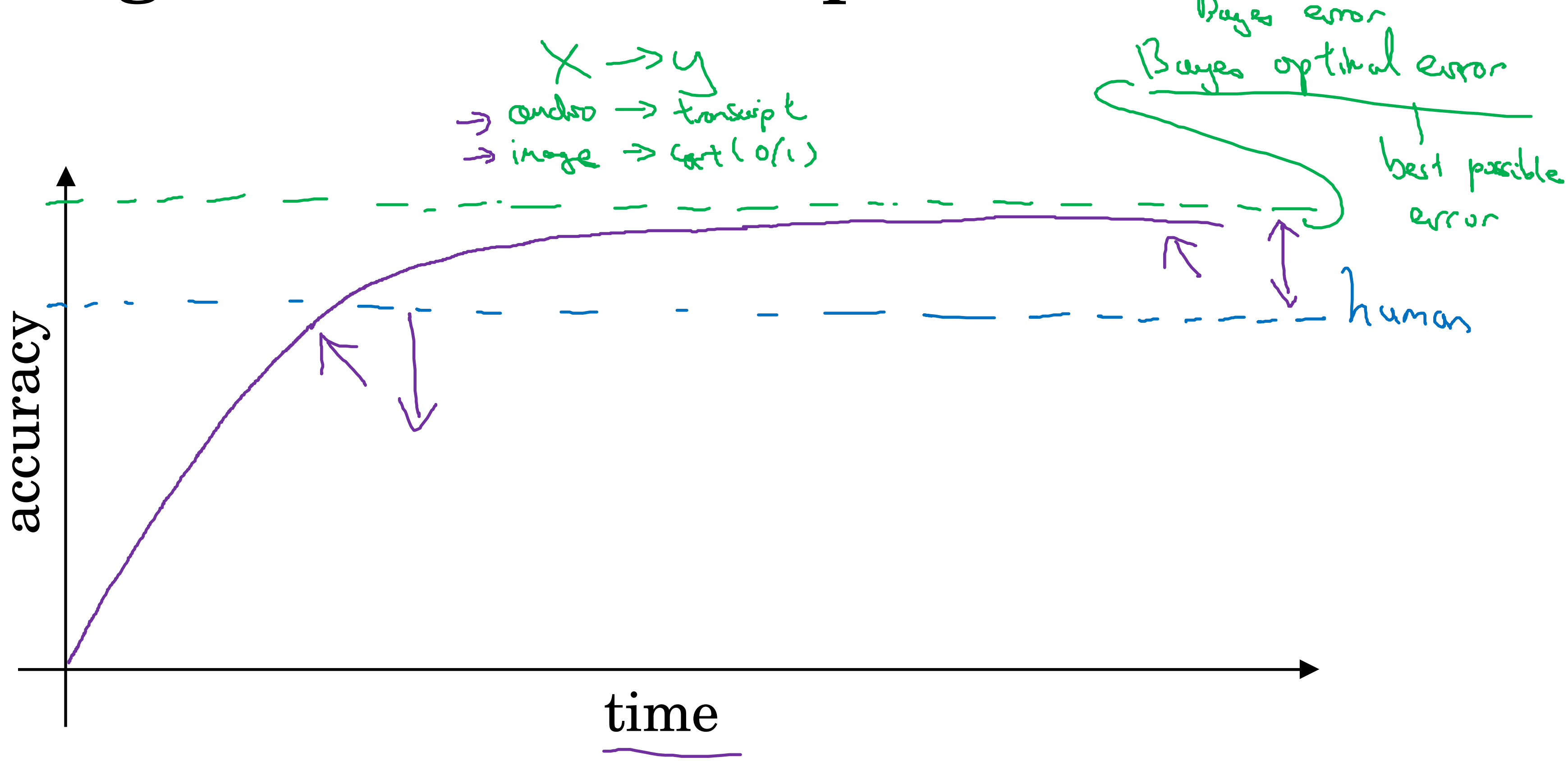
Algorithm B: 5% error

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.

Comparing to human-level performance



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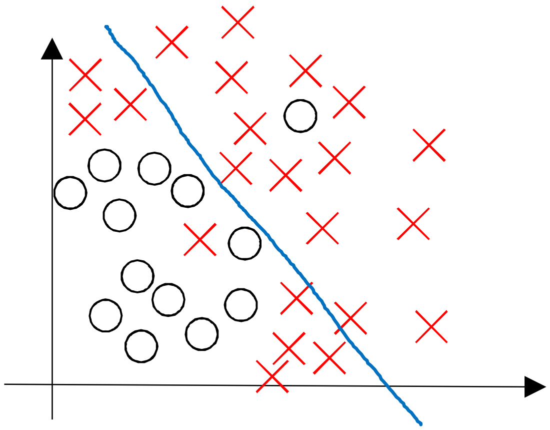
Why compare to human-level performance

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

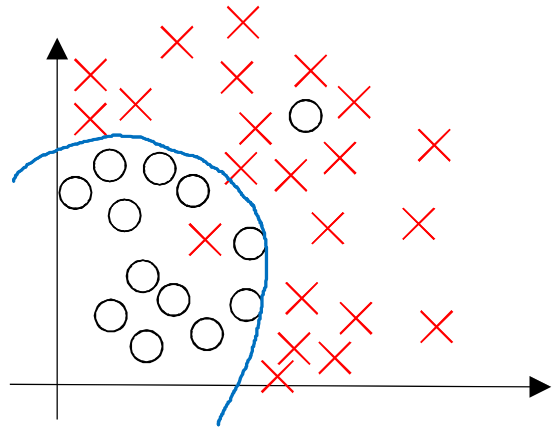
- Get labeled data from humans. (x, y)
- Gain insight from manual error analysis:
  Why did a person get this right?
- Better analysis of bias/variance.

Bias and Variance

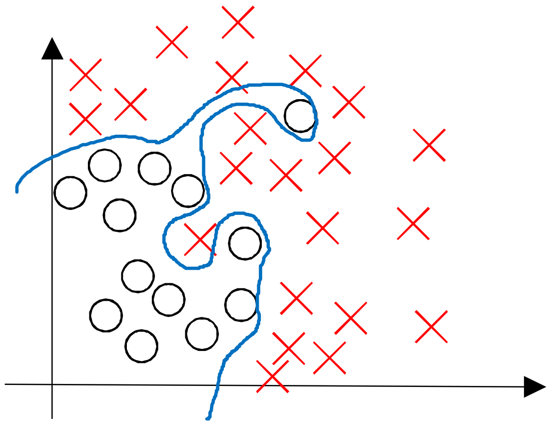


high bias

underfitting



"just right"



high variance

overfitting.

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Bias and Variance

Cat classification

$\boxed{\text{Human-level} \approx 0\%}$ . . . .

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%
	Focus on bias	Focus on variance

7%

2%

0.5%

Avoidable bias

2%

Variance

2%

Variance

Human-level error as a proxy for Bayes error.

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

Bayes error $\leq$ 0.5%

What is "human-level" error?

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Error analysis example

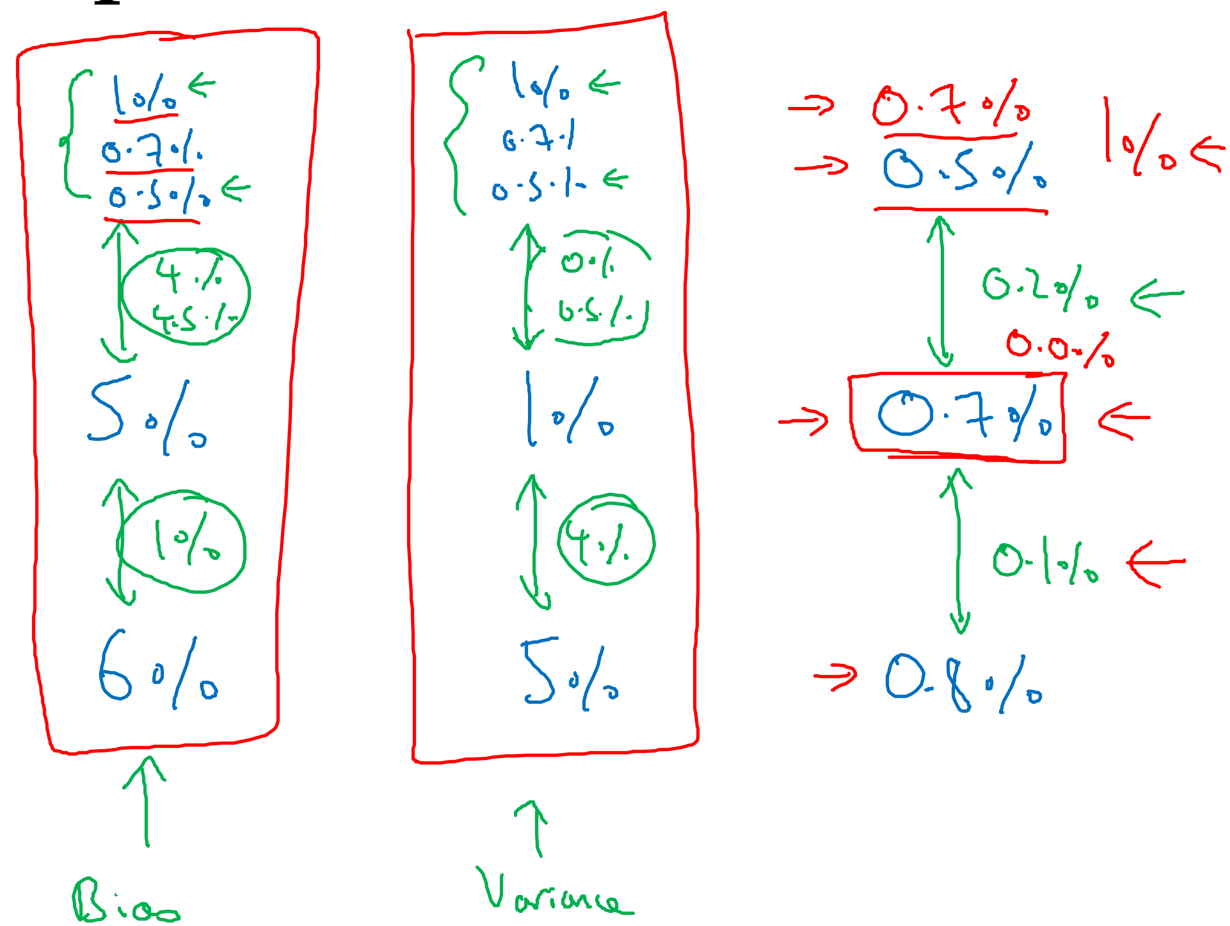
Human (proxy for Bayes error)

Avoidable bias

Training error

Variance

Dev error



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Summary of bias/variance with human-level performance

0%

"Bias"

Human-level error

(proxy for Bayes error)

"Avoidable bias"

Training error

"Variance"

Dev error

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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The two fundamental assumptions of supervised learning

1. You can fit the training set pretty well.

   ~ Avoidable bias

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

   ~ 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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