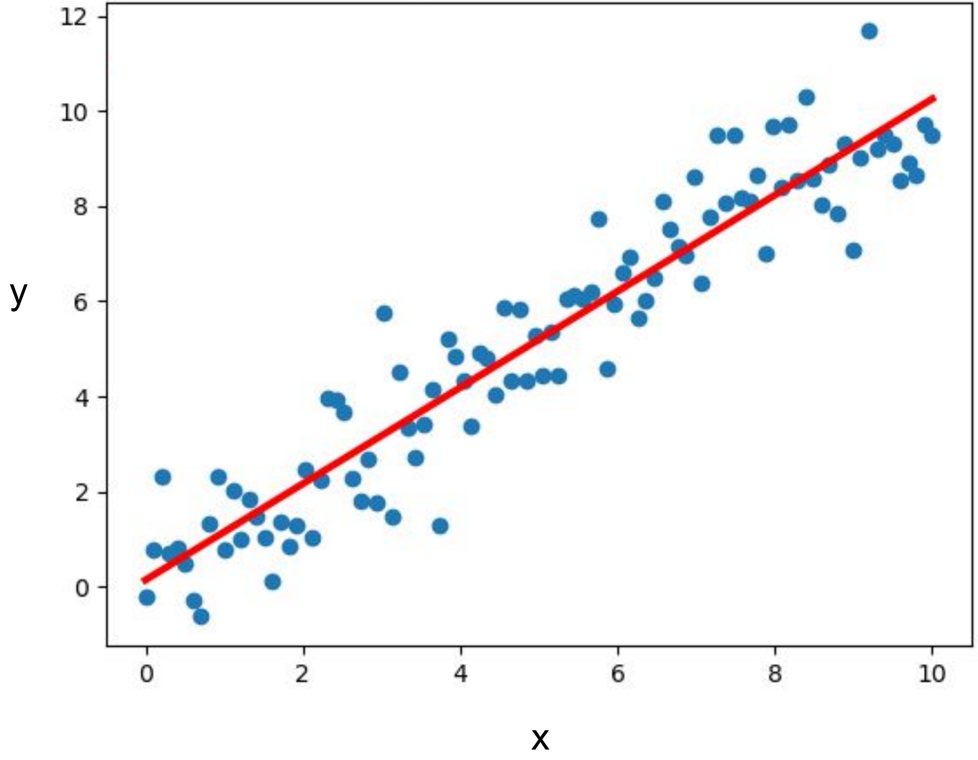
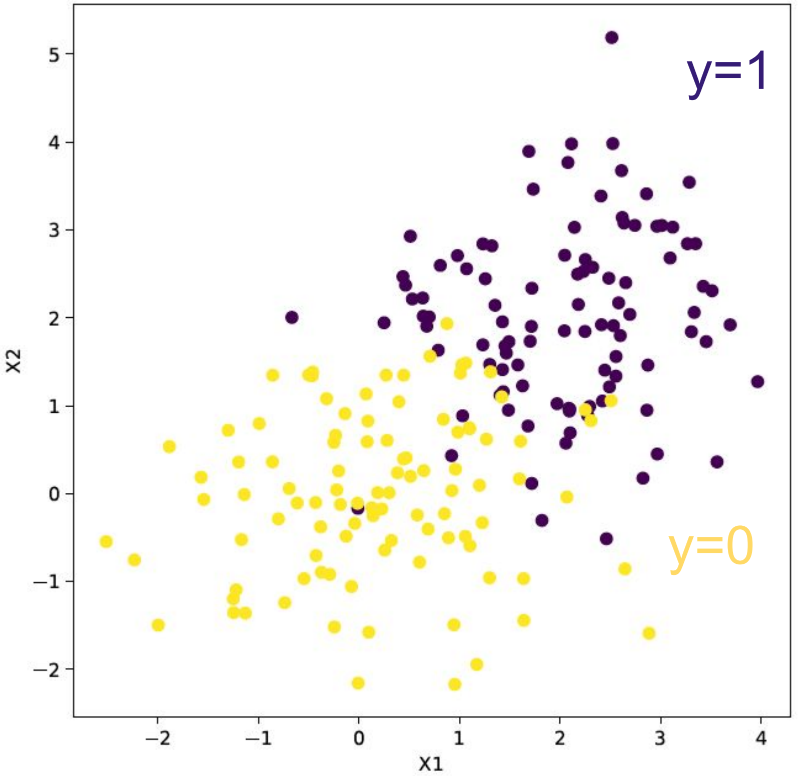
Classification and overfitting

Last time:

regression vs. classification





Last time:

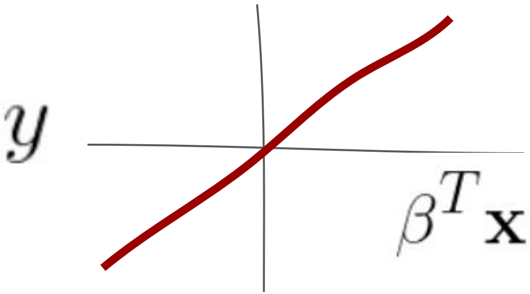
$\mathbf{x}$: vector of k features/covariates/predictors
β : vector of k weights
y : scalar, output/dependent/predicted variable

linear regression: $y = \beta^T \mathbf{x}$

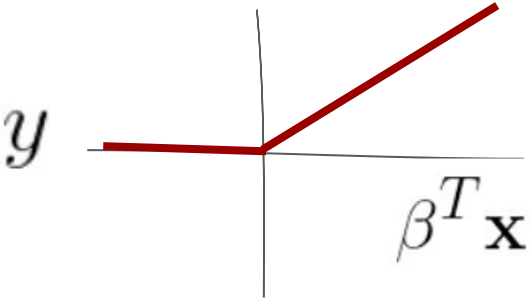
logistic regression: $y = g(\beta^T \mathbf{x})$

Linear and logistic regression are the building blocks for many advanced algorithms, including deep neural networks.

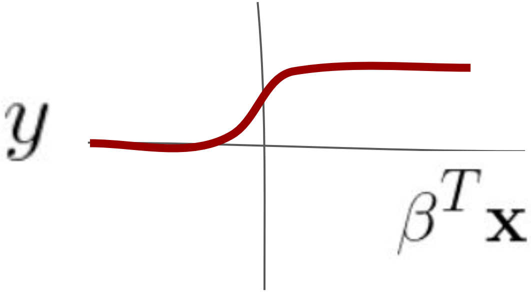
linear function



relu function



logit/sigmoid function



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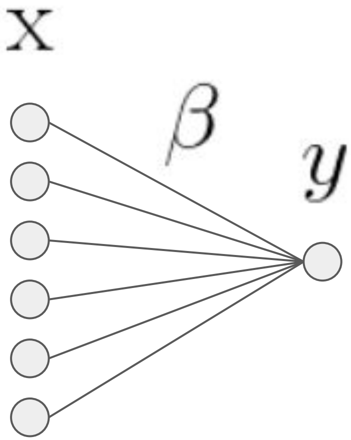
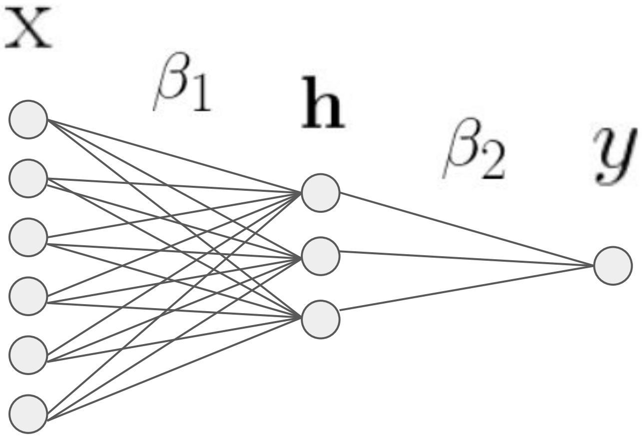
logistic regression:



deep neural network:



Today

- more practice with logistic regression
- training and testing logistic regression

Try section 1 in Colab notebook.

Training and testing in logistic regression.

We want to know how accurate we can predict y.

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Idea:

1. Take data (X, y).
2. Fit Beta.
3. Report accuracy of how well y_hat predicts y.

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Can we trust this reported accuracy?

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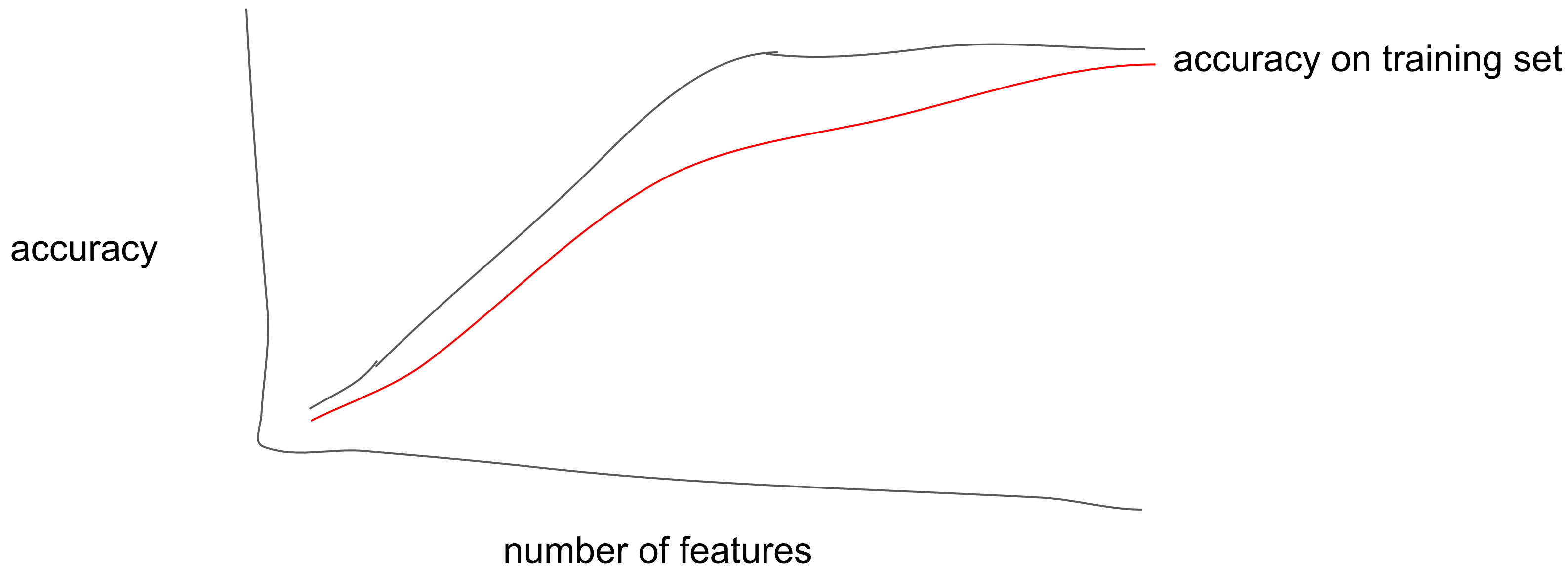
Let’s test this out in the Colab Notebook.


accuracy on training set
accuracy
number of features

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Basic advice:
Given a dataset, split it immediately. Then never touch the test set until you are ready to report accuracy.

Let’s see what happens when we report accuracy on a heldout set (not the training set) in the Colab notebook.