Machine Learning
Linear Classification
Logistic Regression

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Recap

Lecture 2:
Linear Regression

- Linear Models overview
- Regression problem statement
- Linear Regression analytical solution
  - Gauss-Markov theorem (BLUE)
  - Instability
- Regularization
  - L2 aka Ridge
    - Analytical solution
  - L1 aka LASSO
    - Weights decay rule
  - Elastic Net
- Metrics in regression
- Model building cycle
  - Train
  - Validation
  - Test

Outline

- Linear classification
  - margin
  - loss functions
- Logistic regression
  - sigmoid derivation
  - Maximum Likelihood Estimation
  - Logistic loss
  - probability calibration
- Multiclass aggregation strategies
  - One vs Rest
  - One vs One
- Metrics in classification
  - Accuracy, Balanced accuracy
  - Precision, Recall, F-score
  - ROC curve, PR curve, AUC
  - Confusion matrix

Linear Classification

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01

Classification problem

Let's denote:

- Training set $\{(\boldsymbol{x}^{(i)}, y^{(i)})\}_{i=1}^{n}$,where

— $\boldsymbol{x}^{(i)} \in \mathbb{R}^p, y^{(i)} \in \{C_1, \dots, C_K\}$ for classification

- Model $c(\boldsymbol{x})$ predicts class label or classes probability vector for every object
- Loss function $L(\boldsymbol{x}, y, f)$ that should be minimized

Consider binary classification for now:

$$y^{(i)} \in \{+1, -1\}$$

Linear classifier

The most simple linear classifier

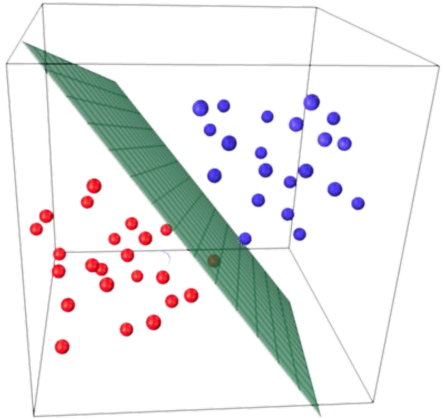
$$c(x) = \begin{cases} 1, & \text{if } f(x) \geq 0 \\ -1, & \text{if } f(x) < 0 \end{cases}$$

or equivalently

$$c(x) = \text{sign}(f(x)) = \text{sign}(x^T w)$$

Why cutoff value is fixed?
(bias term is implied)

Geometrical interpretation:
hyperplane dividing space into
two subspaces



Margin

Let’s define linear model’s Margin as

$$M_i = y_i \cdot f(x_i) = y_i \cdot x_i^T w$$

main property:
negative margin reveals misclassification

$$M_i > 0 \Leftrightarrow y_i = c(x_i)$$
$$M_i \leq 0 \Leftrightarrow y_i \neq c(x_i)$$

Weights choice

Remembering old paradigm

$$\text{Empirical risk} = \sum_{\text{by objects}} \text{Loss on object} \to \min_{\text{model params}}$$

Essential loss is misclassification

$$L_{\text{mis}}(y_i^t, y_i^p) = [y_i^t \neq y_i^p] =$$
$$= [M_i \leq 0]$$

Iverson bracket $[P] = \begin{cases} 1, & \text{if } P \text{ is true} \\ 0, & \text{otherwise} \end{cases}$

Disadvantages

- Not differentiable
- Overlooks confidence

Solution:
estimate it with a smooth function

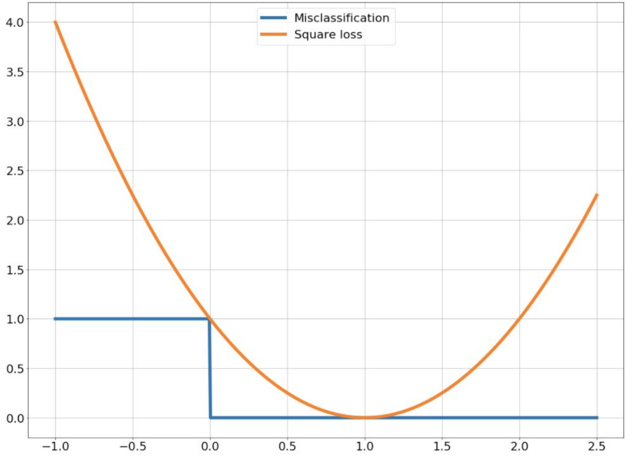
Square loss

Let's treat classification problem as regression problem:

$$Y \in \{-1, 1\} \mapsto Y \in R$$

thus we optimize MSE

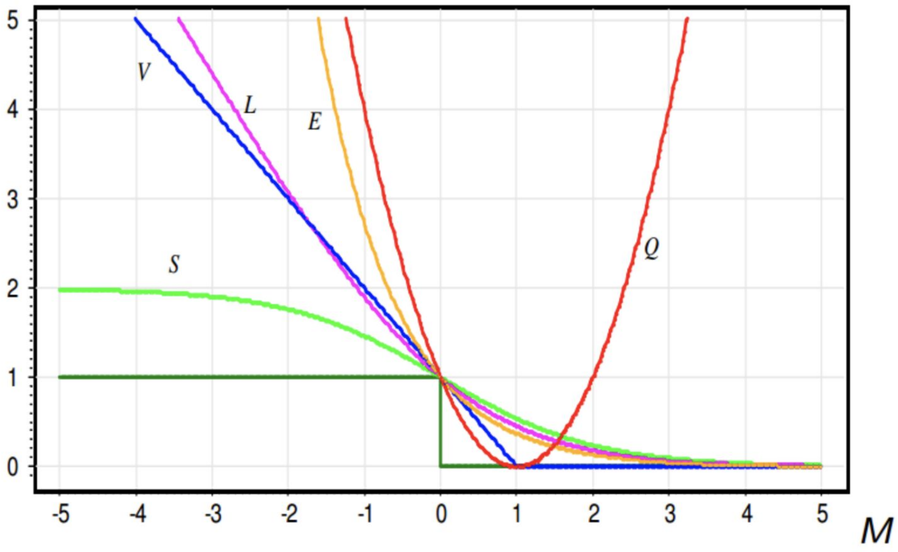
$$L_{\text{MSE}} = (y_i - x_i^T w)^2 = \frac{(y_i^2 - y_i \cdot x_i^T w)^2}{y_i^2} =$$
$$= (1 - y_i \cdot x_i^T w)^2 = (1 - M_i)^2$$



Advantage: already solved

Disadvantage: penalizes for high confidence

Other losses



square loss $Q(M) = (1 - M)^2$

hinge loss $V(M) = (1 - M)_+$

savage loss $S(M) = 2(1 + e^M)^{-1}$

logistic loss $L(M) = \log_2(1 + e^{-M})$

exponential loss $E(M) = e^{-M}$

Loss functions for classification

Logistic Regression

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Intuition

I. Let's try to predict probability of an object to have positive class

$$p_+ = P(y = 1|x) \in [0, 1]$$

II. But all we can predict is a real number!

$$y = x^T w \in \mathbb{R}$$

III. Time for some tricks

$$\frac{p_+}{1 - p_+} \in \mathbb{R}^+$$

$$\log \frac{p_+}{1 - p_+} \in \mathbb{R}$$

IV. Reverse to closed form

$$\frac{p_+}{1 - p_+} = \exp(x^T w) \in \mathbb{R}^+$$

Here is the match

$$p_+ = \frac{1}{1 + exp(-x^T w)} = \sigma(x^T w)$$

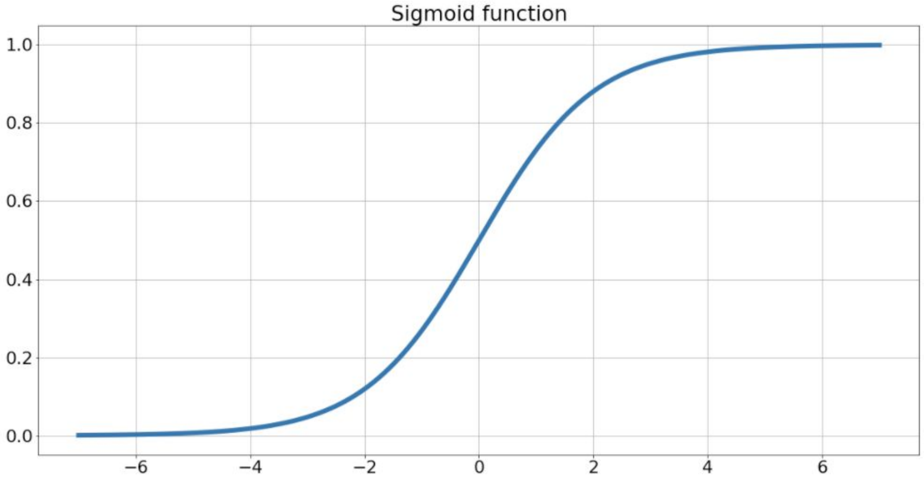
Sigmoid (aka logistic) function

$$\sigma(x) = \frac{1}{1 + exp(-x)}$$

Sigmoid is odd relative to (0, 0.5) point

Symmetric property:

$$1 - \sigma(x) = \sigma(-x)$$



Derivative: $$\sigma'(x) = \sigma(x) \cdot (1 - \sigma(x))$$

Maximum Likelihood Estimation

Just to remind

$$\log L(w|X,Y) = \log P(X,Y|w) = \log \prod_{i=1}^{n} P(x_i, y_i|w)$$

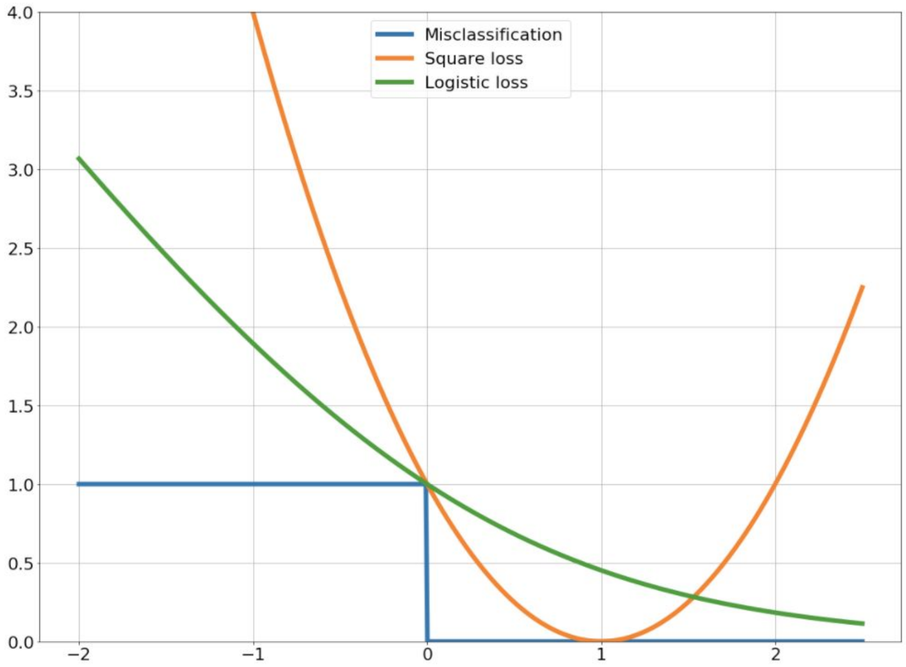
Calculating probabilities for objects

$$\text{if } y_i = 1: \quad P(x_i, 1|w) = \sigma_w(x_i) = \sigma_w(M_i)$$
$$\text{if } y_i = -1: \quad P(x_i, -1|w) = 1 - \sigma_w(x_i) = \sigma_w(-x_i) = \sigma_w(M_i)$$

$$\log L(w|X,Y) = \sum_{i=1}^{n} \log \sigma_w(M_i) \boxed{= -\sum_{i=1}^{n} \log(1 + \exp(-M_i)) \to \max_w}$$

Logistic loss

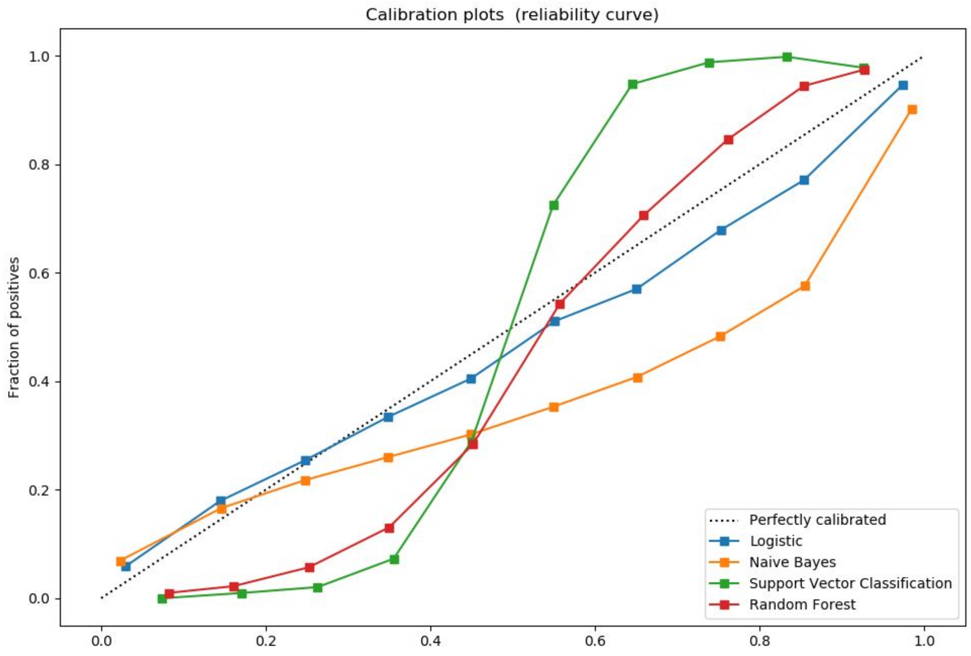
$$L_{Logistic} = \log(1 + \exp(-M_i))$$



Probability calibration

By using Logistic Regression we generate a Bernoulli distribution in each point of space

Calibration discussion



Multiclass aggregation strategies

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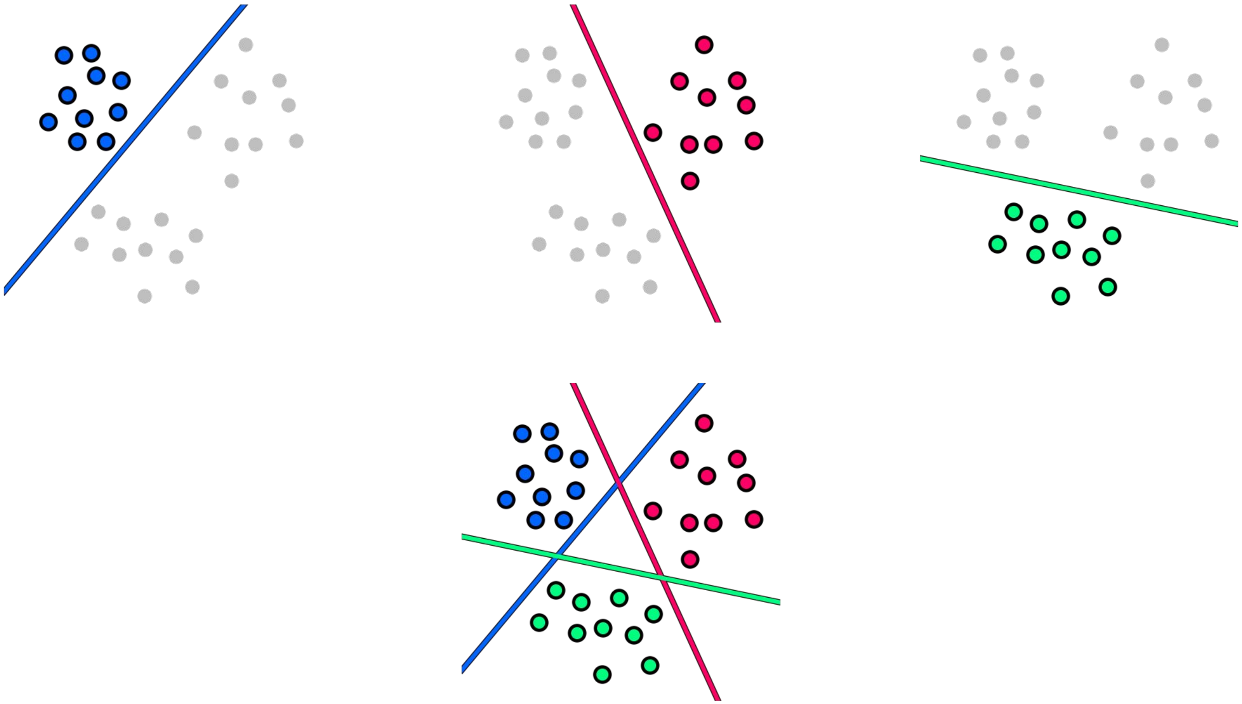
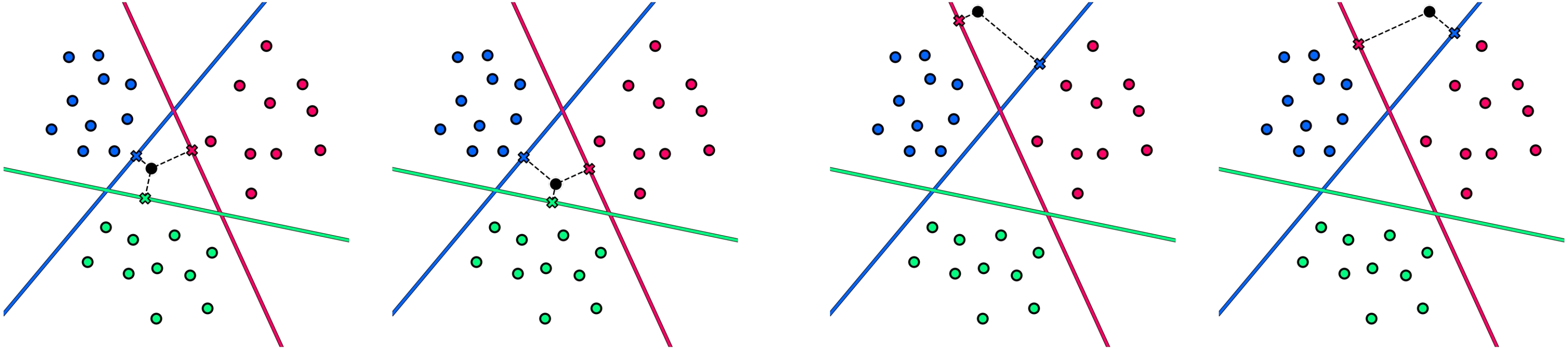
One vs Rest

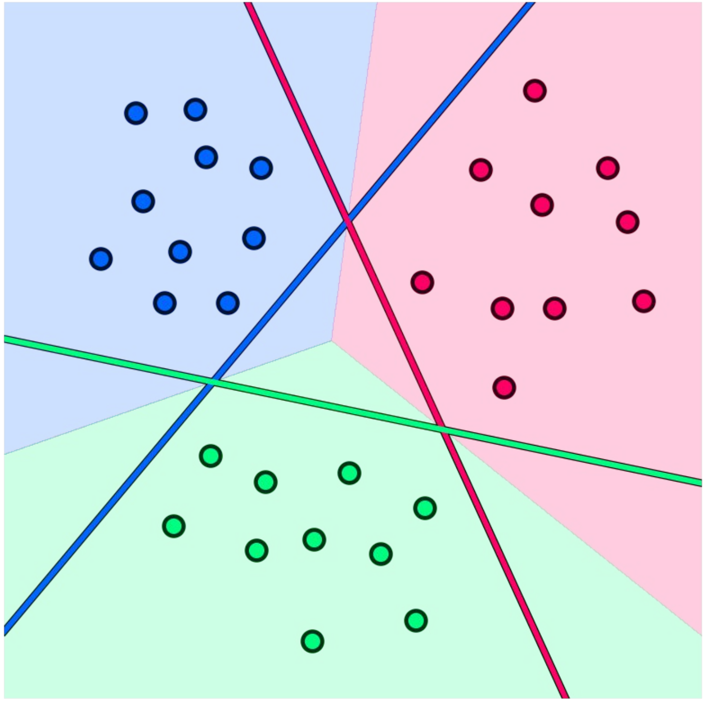


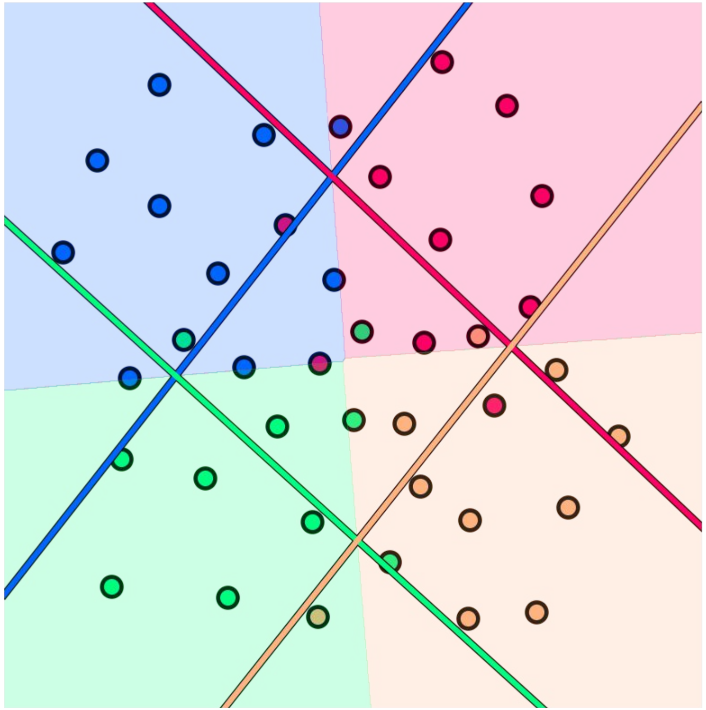
Images source

One vs Rest: unclassified regions

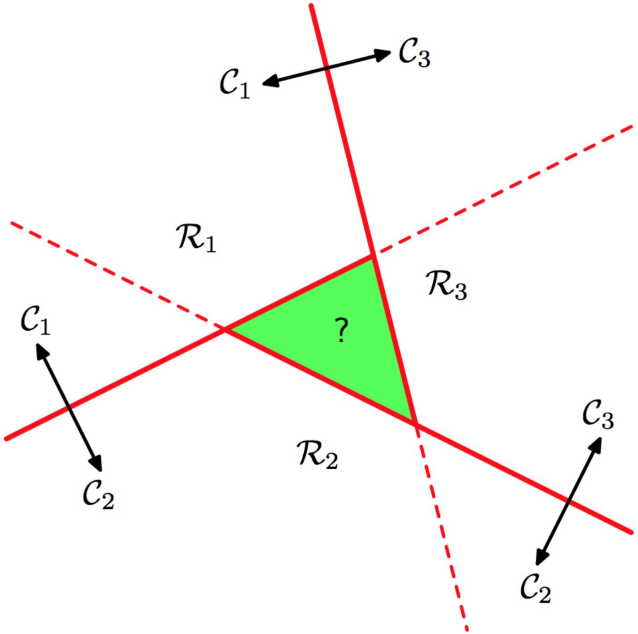


One vs Rest: final result



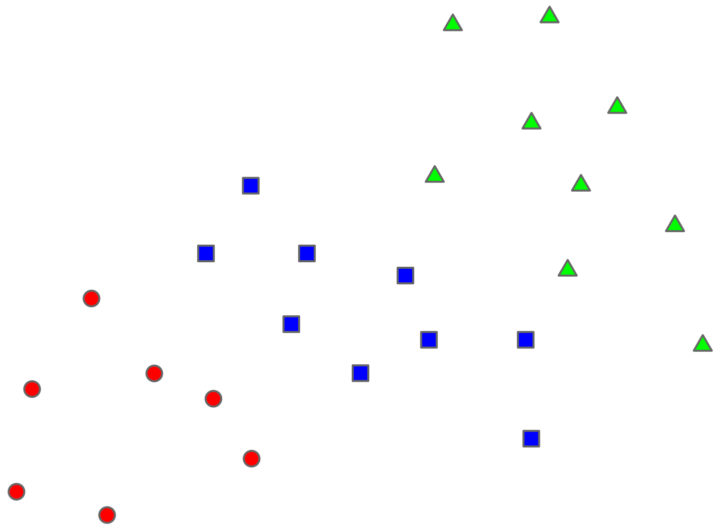


One vs One



$\mathcal{C}_1$
$\mathcal{C}_3$
$\mathcal{R}_1$
$\mathcal{R}_3$
$\mathcal{C}_1$
?
$\mathcal{C}_3$
$\mathcal{R}_2$
$\mathcal{C}_2$
$\mathcal{C}_2$

Failure case?



Summary

	One vs Rest	One vs One
#classifiers	k	k(k-1)/2
dataset for each	full	subsampled

Metrics in classification

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Metrics

- Accuracy
  - Balanced accuracy
- Precision
- Recall
- F-score
- ROC curve
  - ROC-AUC
- PR curve
  - PR-AUC
- Multiclass generalizations
- Confusion matrix

Accuracy

Number of right classifications

$$\text{Accuracy} = \frac{1}{n}\sum_{i=1}^{n}[y_i^t = y_i^p]$$

target: 1 0 1 0 0 0 0 1 0 0

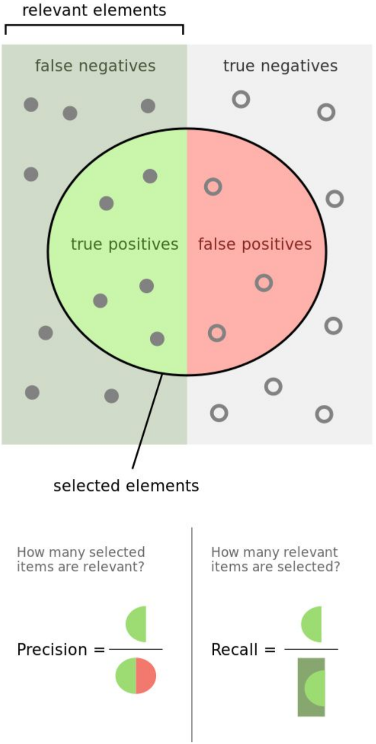
predicted: 0 0 1 0 0 0 0 1 1 0

accuracy = 8/10 = 0.8

$$\text{Balanced accuracy} = \frac{1}{C}\sum_{k=1}^{C}\frac{\sum_i [y_i^t = k \text{ and } y_i^t = y_i^p]}{\sum_i [y_i^t = k]}$$

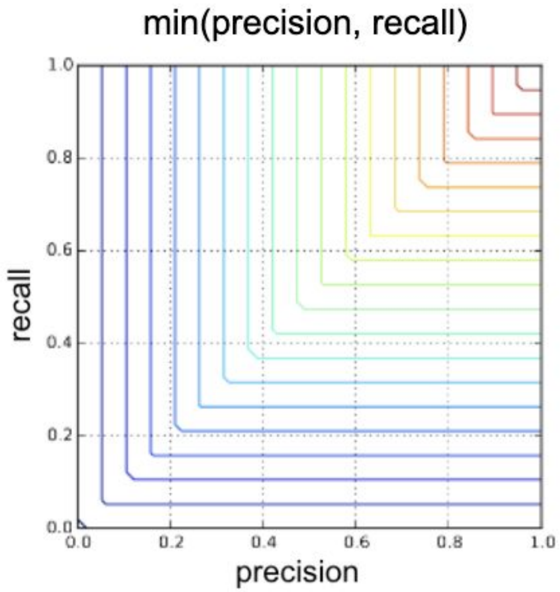
Precision and Recall

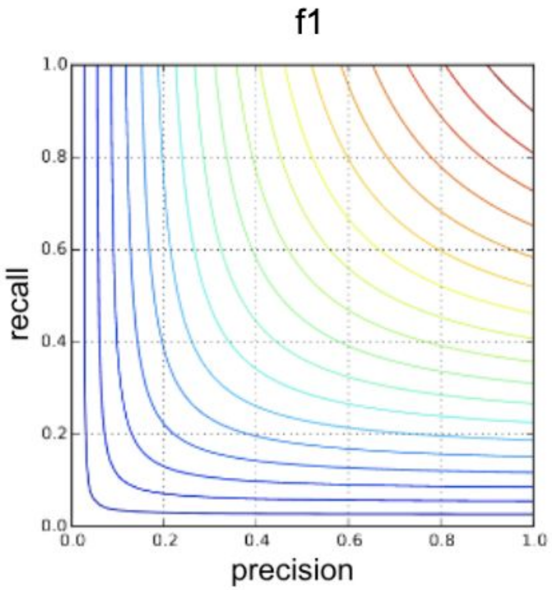
		True condition	
	Total population	Condition positive	Condition negative
Predicted condition	Predicted condition positive	**True positive**	**False positive**, Type I error
	Predicted condition negative	**False negative**, Type II error	**True negative**



$$\text{Precision} = \frac{TP}{TP + FP} \quad \text{Recall} = \frac{TP}{TP + FN}$$

F-score motivation





F-score

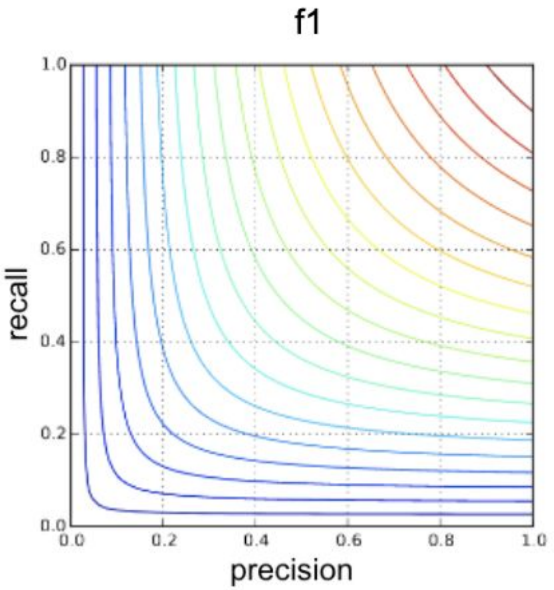
Harmonic mean of precision and recall

Closer to smaller one

$$F_1 = \frac{2}{\text{precision}^{-1} + \text{recall}^{-1}} = 2\,\frac{\text{precision} \cdot \text{recall}}{\text{precision} + \text{recall}}$$

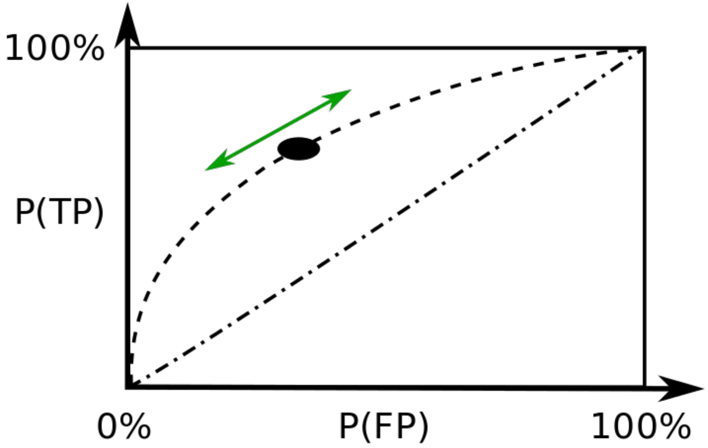
Generalization to different ratio between Precision and Recall

$$F_\beta = (1 + \beta^2)\,\frac{\text{precision} \cdot \text{recall}}{\beta^2\,\text{precision} + \text{recall}}$$



Receiver Operating Characteristic (ROC)

		True condition	
	Total population	Condition positive	Condition negative
Predicted condition	Predicted condition positive	**True positive**	**False positive**, Type I error
	Predicted condition negative	**False negative**, Type II error	**True negative**



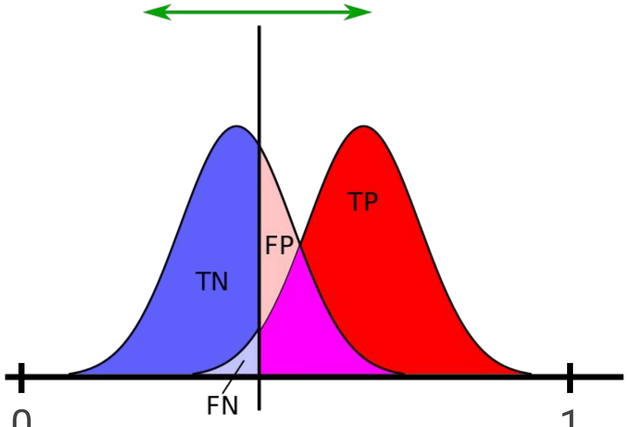
$$\mathrm{FPR} = \frac{FP}{FP + TN}$$

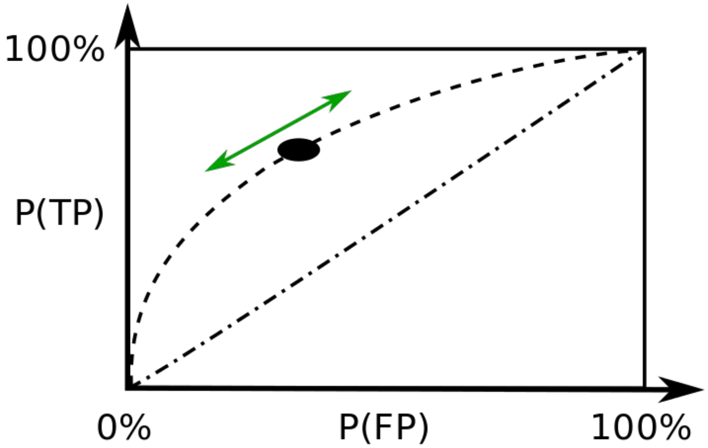
$$\mathrm{TPR} = \frac{TP}{TP + FN} (= \mathrm{Recall})$$

Receiver Operating Characteristic (ROC)

Classifier needs to predict probabilities

Objects get sorted by positive probability





Line is plotted as threshold moves

Receiver Operating Characteristic (ROC)

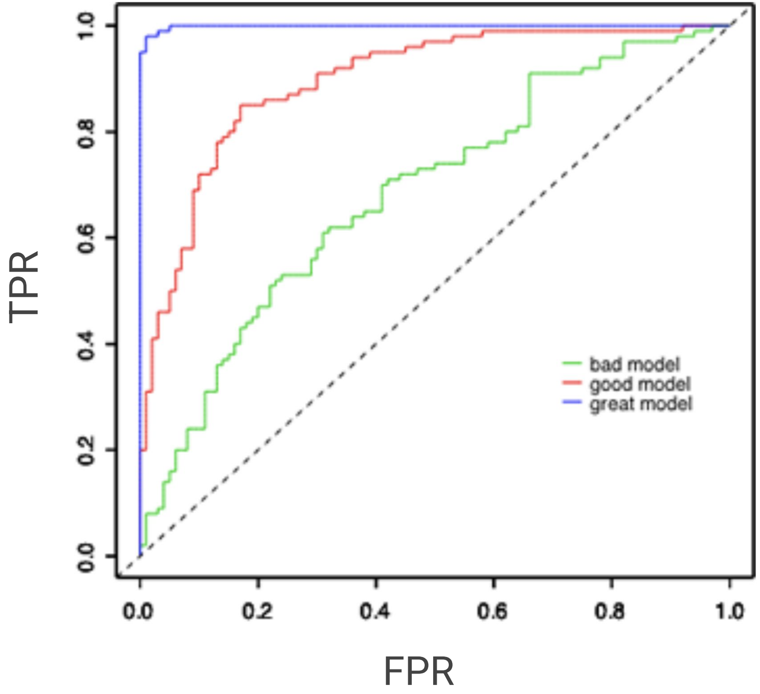
Baseline is random predictions

Always above diagonal (for reasonable classifier)

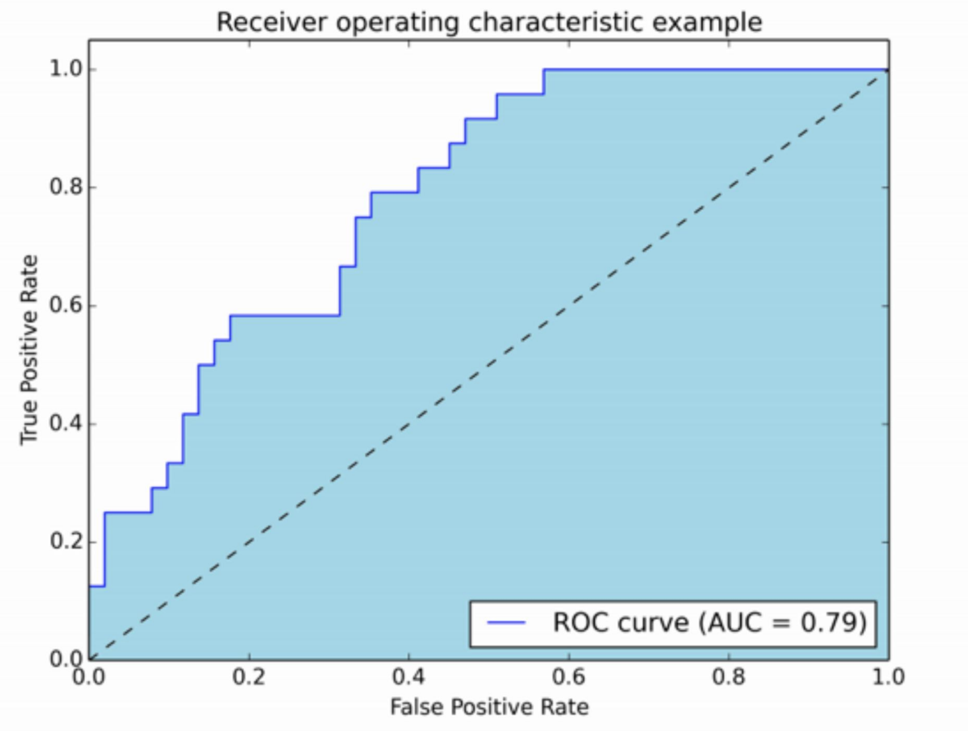
If below - change sign of predictions

Strictly higher curve means better classifier

Number of steps (thresholds) not bigger than dataset



ROC Area Under Curve (ROC-AUC)



Effectively lays in (0.5, 1)

Bigger ROC-AUC doesn't imply

higher curve everywhere

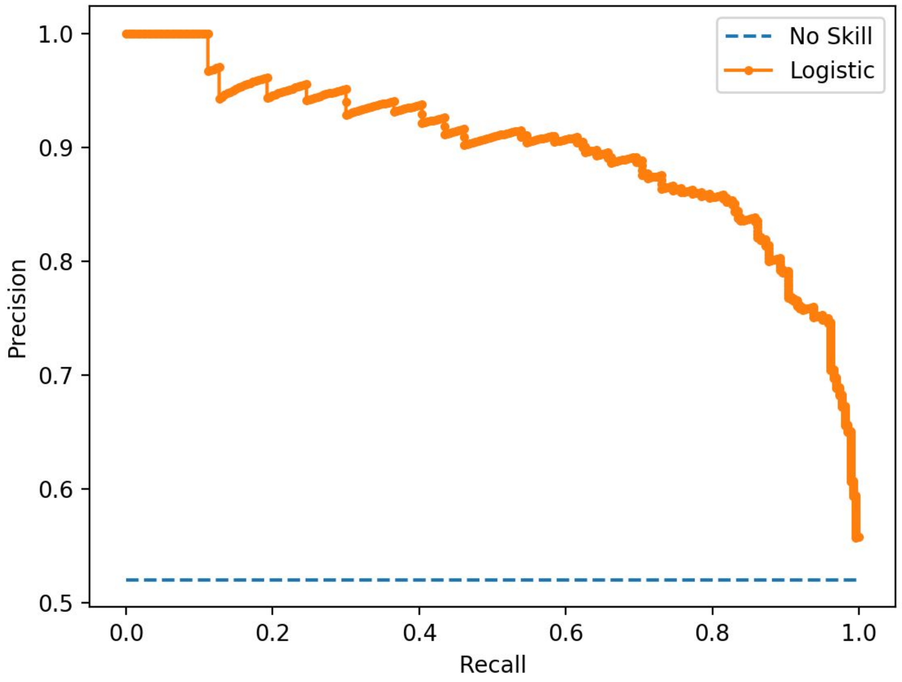
[More explanations with pictures]

Precision-Recall Curve

AUC is in (0, 1)

Source of AP metric
(important for next semester)

Nice article



Multiclass metrics

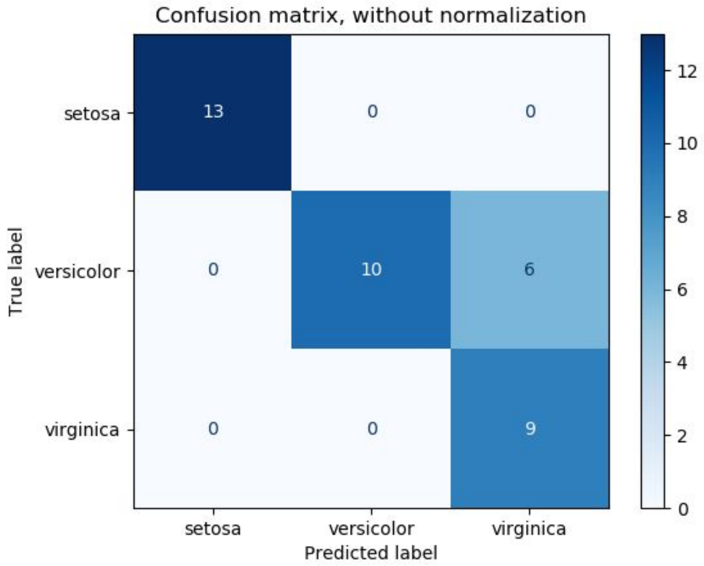
As with linear models we need some magic to measure multiclass problems

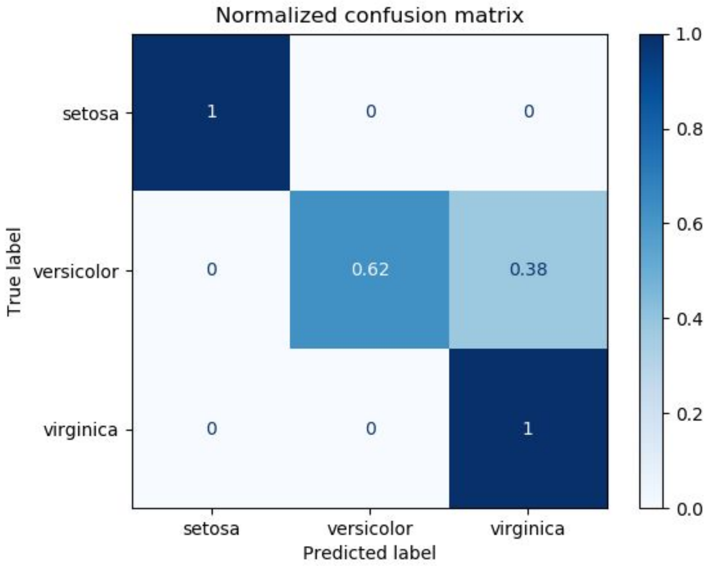
Basically it's mean of one or another kind

Detailed info here and here

average	Precision	Recall	F_beta
"micro"	$P(y, \hat{y})$	$R(y, \hat{y})$	$F_\beta(y, \hat{y})$
"samples"	$\frac{1}{\|S\|} \sum_{s \in S} P(y_s, \hat{y}_s)$	$\frac{1}{\|S\|} \sum_{s \in S} R(y_s, \hat{y}_s)$	$\frac{1}{\|S\|} \sum_{s \in S} F_\beta(y_s, \hat{y}_s)$
"macro"	$\frac{1}{\|L\|} \sum_{l \in L} P(y_l, \hat{y}_l)$	$\frac{1}{\|L\|} \sum_{l \in L} R(y_l, \hat{y}_l)$	$\frac{1}{\|L\|} \sum_{l \in L} F_\beta(y_l, \hat{y}_l)$
"weighted"	$\frac{1}{\sum_{l \in L} \|\hat{y}_l\|} \sum_{l \in L} \|\hat{y}_l\| P(y_l, \hat{y}_l)$	$\frac{1}{\sum_{l \in L} \|\hat{y}_l\|} \sum_{l \in L} \|\hat{y}_l\| R(y_l, \hat{y}_l)$	$\frac{1}{\sum_{l \in L} \|\hat{y}_l\|} \sum_{l \in L} \|\hat{y}_l\| F_\beta(y_l, \hat{y}_l)$

Confusion matrix





Revise

- Linear classification
  - margin
  - loss functions
- Logistic regression
  - sigmoid derivation
  - Maximum Likelihood Estimation
  - Logistic loss
  - probability calibration
- Multiclass aggregation strategies
  - One vs Rest
  - One vs One
- Metrics in classification
  - Accuracy, Balanced accuracy
  - Precision, Recall, F-score
  - ROC curve, PR curve, AUC
  - Confusion matrix

Next time

- Support Vector Machines
- Principal Component Analysis
- Linear Discriminant Analysis

Thanks for attention!

Questions?

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