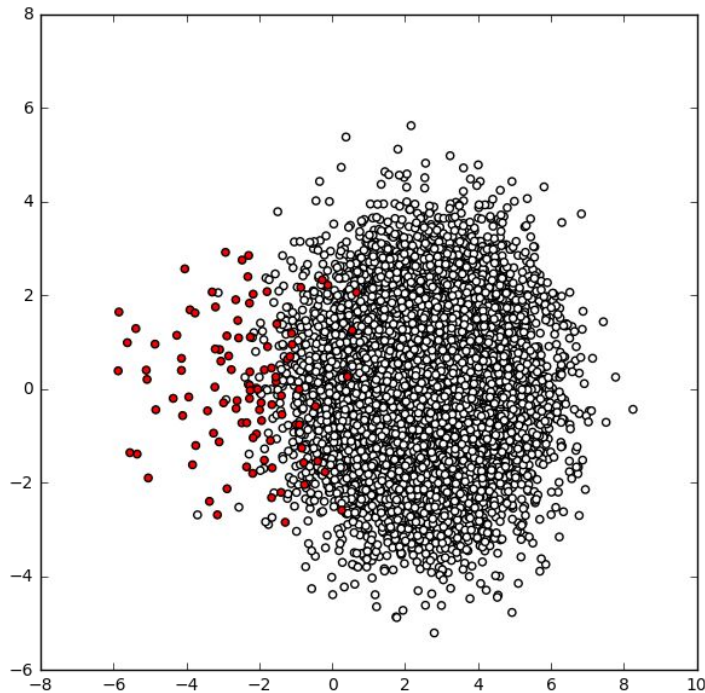


Profit Curves & Imbalanced Classes

Galvanize, Seattle
jfomhover

*Credits: drawing on work from Ryan Henning, Ivan Corneillet,
Darren Reger...*





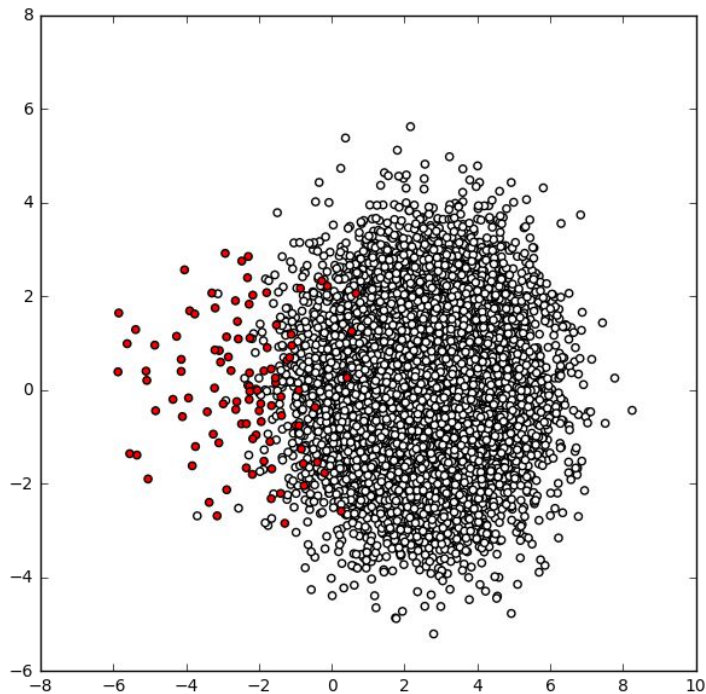
Profit Curves & Imbalanced Classes

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OBJECTIVES

- **Discuss** and give examples of the issues with imbalanced classes.
- **Explain** and **implement** the profit curve method.
- **Explain** cost sensitive learning and how it deals with imbalanced classes.
- **Define**, give examples and relate sampling methods.

Imbalanced Classes: failure analysis

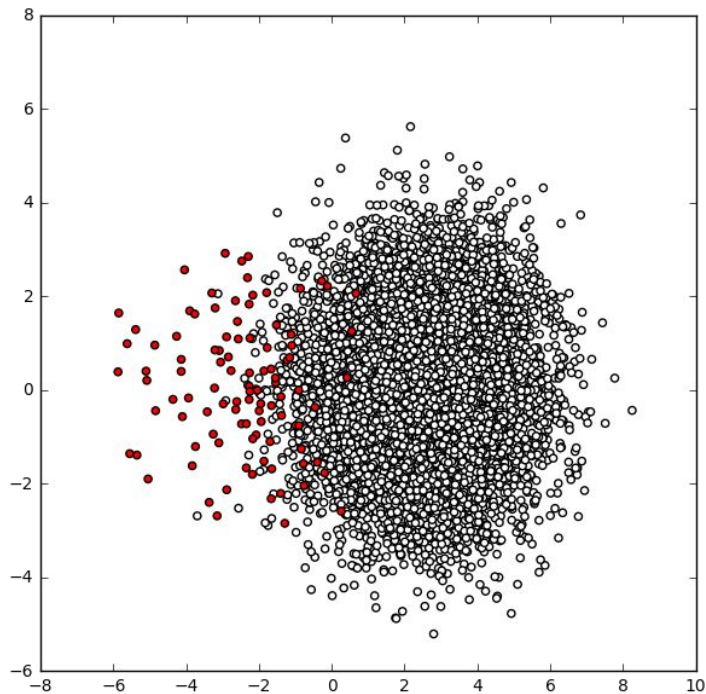


Example : 100 pos, 10000 neg

Pb : what could it change during LEARNING ?

Pb: what could it change during EVALUATION ?

Imbalanced Classes: failure analysis



Example : 100 pos, 10000 neg

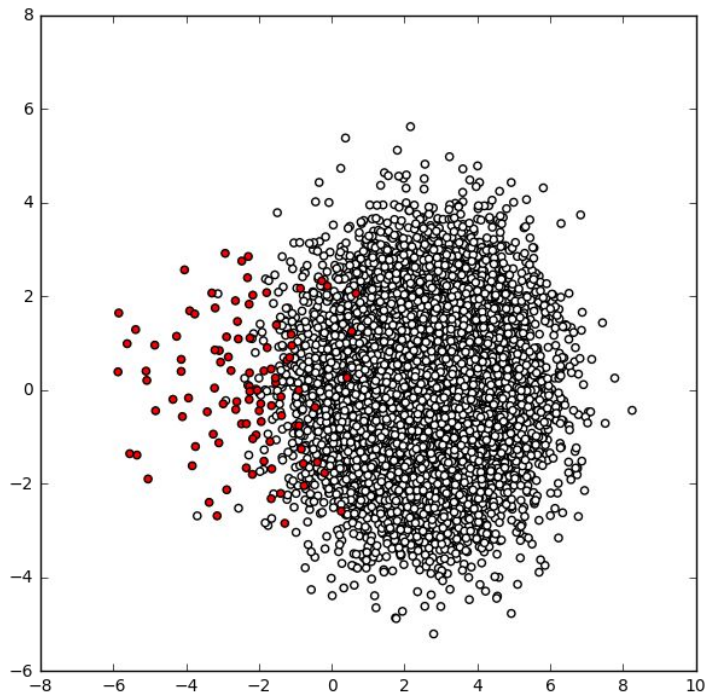
Pb : what could it change during LEARNING ?

**Sol: cost-sensitive learning,
over/under sampling**

Pb: what could it change during EVALUATION ?

Sol: cost-benefit matrix

Imbalanced Classes during EVALUATION



I can design a classifier with 99% accuracy !

Accuracy-driven models will over-predict the majority class.

Example : 100 pos, 10000 neg

QUESTION: how would you pick your favorite matrix ?



A	Pred:	
	pos	neg
Actual: pos	12	8
Actual: neg	15	965

B	Pred:	
	pos	neg
Actual: pos	0	20
Actual: neg	0	980

C	Pred:	
	pos	neg
Actual: pos	15	5
Actual: neg	115	865

D	Pred:	
	pos	neg
Actual: pos	18	2
Actual: neg	250	730

QUESTION: how would you pick your favorite matrix ?



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Actual: neg	15	965

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DEFINE A BUSINESS PROBLEM

QUESTION: how would you pick your favorite matrix ?



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FORMALIZE COSTS AND BENEFITS
DEFINE A BUSINESS PROBLEM

Confusion Matrix



	Pred: Y	Pred: N
Actual: y	TP	FN
Actual: n	FP	TN


Confusion Matrix

$P = TP + FN$ = count of actual y

$N = FP + TN$ = count of actual n

VALUES ARE COUNTS

Probability Matrix



	Pred: Y	Pred: N
Actual: y	TP	FN
Actual: n	FP	TN

	Pred: Y	Pred: N
Actual: y	$p(Y,y)$	$p(N,y)$
Actual: n	$p(Y,n)$	$p(N,n)$

Confusion Matrix

$P = TP + FN = \text{count of actual } y$

$N = FP + TN = \text{count of actual } n$

Probability Matrix

$p(Y,y) = TP / (P + N)$

$p(Y,n) = FP / (P + N)$


$p(N,y) = FN / (P + N)$

$p(N,n) = TN / (P + N)$

VALUES ARE COUNTS

VALUES ARE PROBAS

Cost-Benefit Matrix



	Pred: Y	Pred: N
Actual: y	TP	FN
Actual: n	FP	TN

Confusion Matrix

$P = TP + FN = \text{count of actual } y$
 $N = FP + TN = \text{count of actual } n$

VALUES ARE COUNTS

	Pred: Y	Pred: N
Actual: y	$p(Y,y)$	$p(N,y)$
Actual: n	$p(Y,n)$	$p(N,n)$

Probability Matrix

$p(Y,y) = TP / (P + N)$
 $p(Y,n) = FP / (P + N)$
 $p(N,y) = FN / (P + N)$
 $p(N,n) = TN / (P + N)$

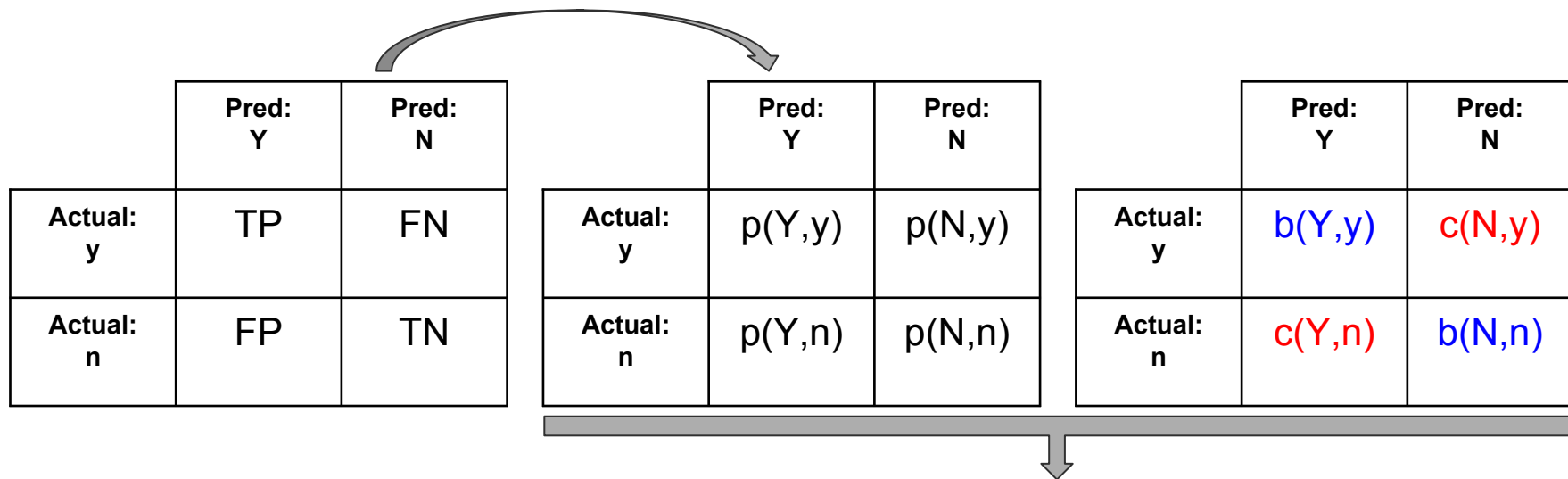
VALUES ARE PROBAS

	Pred: Y	Pred: N
Actual: y	$b(Y,y)$	$c(N,y)$
Actual: n	$c(Y,n)$	$b(N,n)$

Cost-Benefit Matrix

VALUES ARE \$\$\$!

Computing the Expected Profit



$$E[Profit] = p(Y, y).b(Y, y) + p(Y, n).c(Y, n) \\ + p(N, y).c(N, y) + p(N, n).b(N, n)$$

$$= p(Y | y).p(y).b(Y, p) + p(Y | n).p(n).c(Y, n) \\ + p(N | y).p(y).c(N, y) + p(N | n).p(n).b(N, n)$$

$$= p(y).[p(Y | y).b(Y, p) + p(N | y).c(N, y)] \\ + p(n)[p(Y | n).c(Y, n) + p(N | n).b(N, n)]$$

Cost-Benefit Matrix (example 1)



Prompt: You are building a model to predict if credit card charges are fraudulent.

- If we predict a fraudulent charge, we'll call the customer to confirm.
- If you miss a fraudulent charge, it on average costs \$100
- Calling someone to confirm if their charge was real costs on average \$4

Question: What is an appropriate cost benefit matrix?

A	Predicted: fraud	Predicted: not fraud
	Actual: fraud	Actual: not fraud
	96	-100
	-4	0

B	Predicted: fraud	Predicted: not fraud
	Actual: fraud	Actual: not fraud
	-4	-100
	-4	0

C	Predicted: fraud	Predicted: not fraud
	Actual: fraud	Actual: not fraud
	96	0
	-4	0

Cost-Benefit Matrix (example 2)



You are building a model to **predict if customers will churn** from your online clothing store.

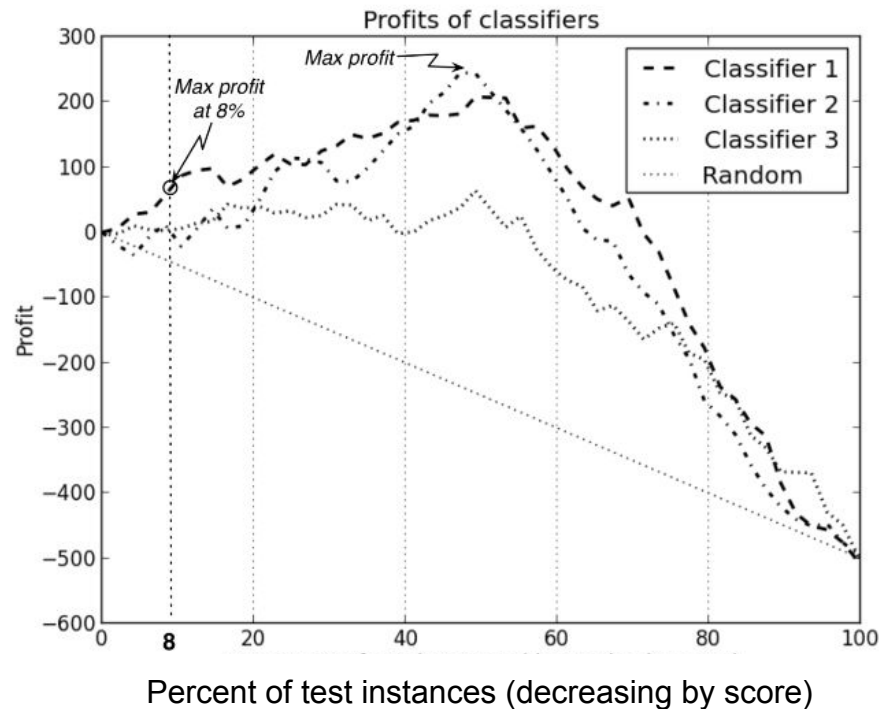
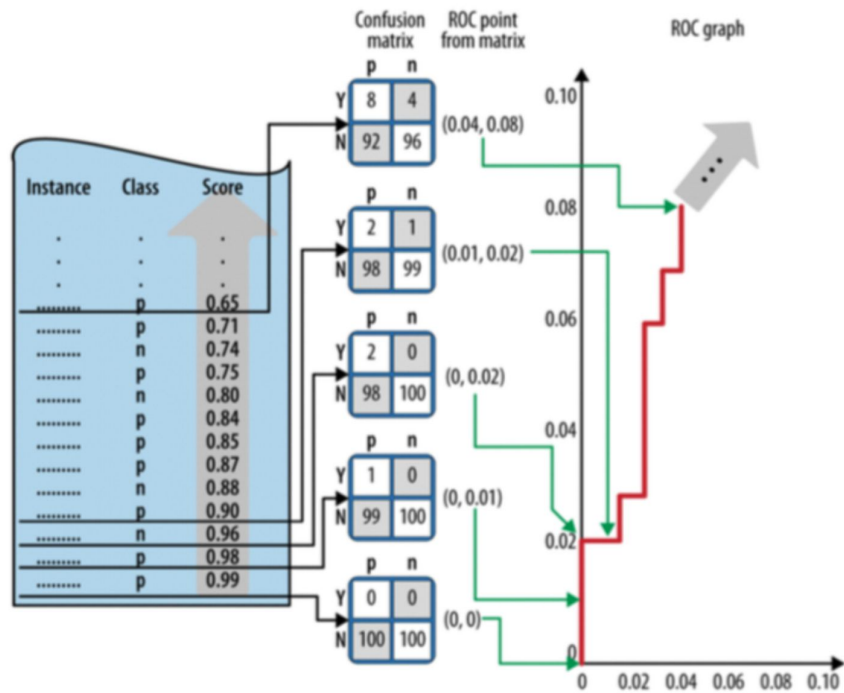
You'll use your model **to send a promotional email** to users you think are going to churn.

You'd like to use a cost benefit matrix so you can build **profit curves to determine the optimal model**.

- Customers on average spend **\$200/month**.
Your profit is **10%** of this revenue.
- A promotional email costs on average **\$2/customer** and prevents **50%** of users from churning for **6 months**.
- When the promotional email is sent to users who were not going to churn, it annoys **5%** of them and causes them to churn **2 months** earlier than they otherwise would have.

	Predicted: churn	Predicted: not churn
Actual: churn	?	?
Actual: Not churn	?	?

From Thresholding to Profit Curves

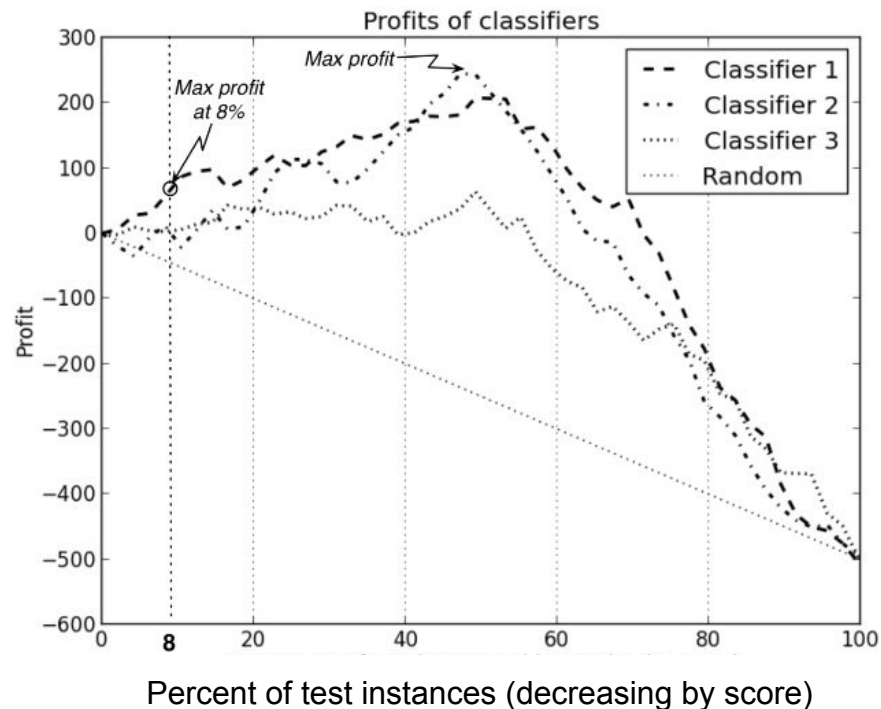


Compare classifiers on one given cost benefit matrix

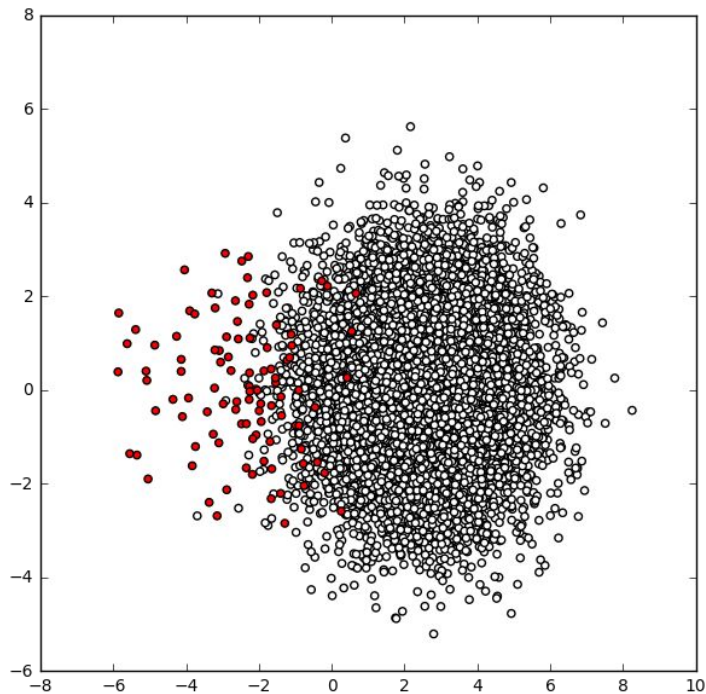


Profit Curve:

- Same idea as ROC curve but with expected profit
- For each threshold, compute the expected profit



Imbalanced Classes: failure analysis



Example : 100 pos, 10000 neg

Pb : what could it change during LEARNING ?

**Sol: cost-sensitive learning,
over/under sampling**

Pb: what could it change during EVALUATION ?

Sol: cost-benefit matrix

Compare classifiers on one given cost benefit matrix

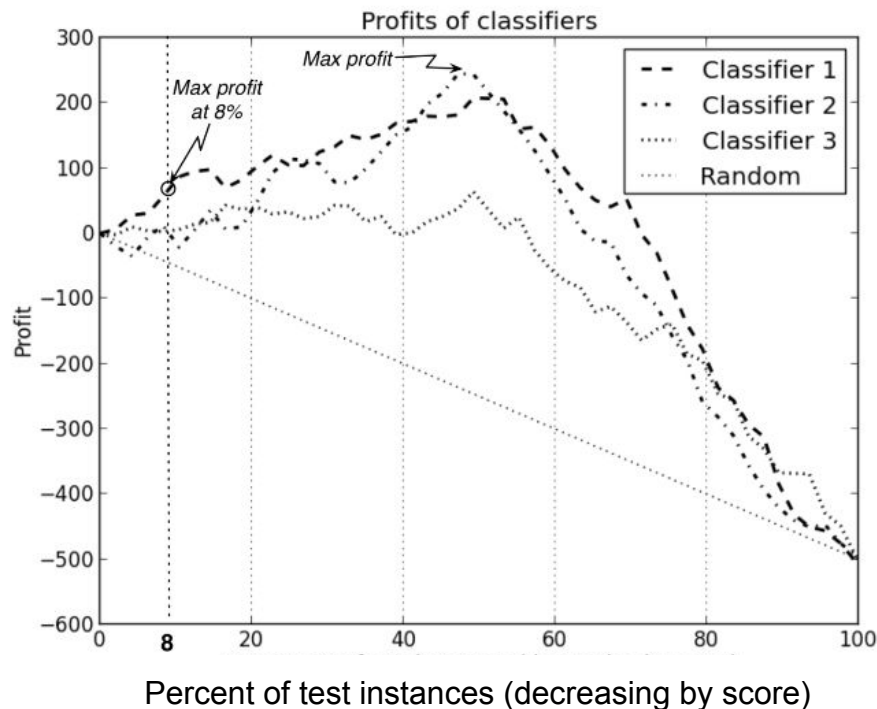


Profit Curve:

- Same idea as ROC curve but with expected profit
- For each threshold, compute the expected profit

Cost-sensitive learning:

- Select threshold with highest expected profit.



Introducing cost-benefit in the objective function



- Models with explicit objective function can be modified to incorporate classification cost.

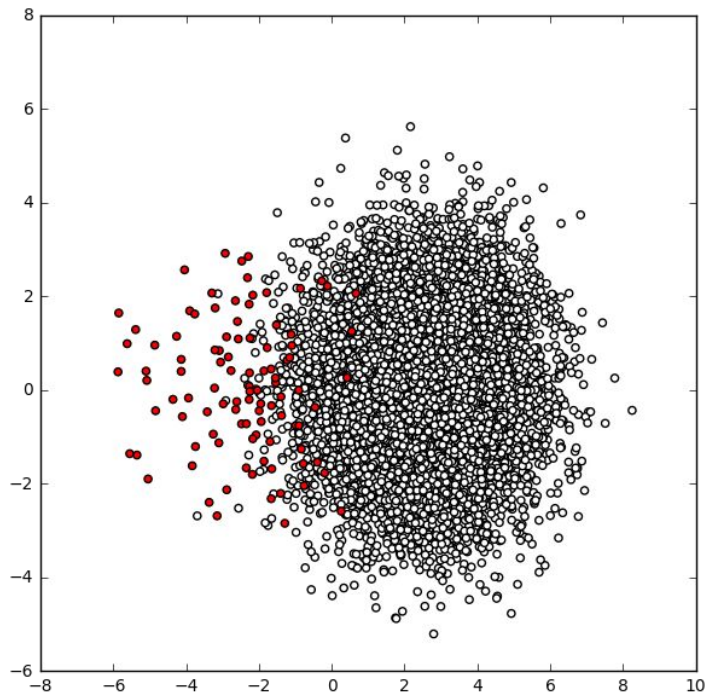
$$\ln p(\vec{y}|X; \theta) = \sum_{i=1}^n (y_i \ln h_{\theta}(x_i) + (1 - y_i) \ln(1 - h_{\theta}(x_i)))$$

- e.g. logistic regression
This will affect optimization.

$$J^c(\theta) = \frac{1}{N} \sum_{i=1}^N \left(y_i (h_{\theta}(X_i) C_{TP_i} + (1 - h_{\theta}(X_i)) C_{FN_i}) \right. \\ \left. + (1 - y_i) (h_{\theta}(X_i) C_{FP_i} + (1 - h_{\theta}(X_i)) C_{TN_i}) \right).$$

- cost-sensitive logistic regression
may not be convex anymore !
- Not all models have a cost-sensitive implementation.

Imbalanced Classes: failure analysis



Example : 100 pos, 10000 neg

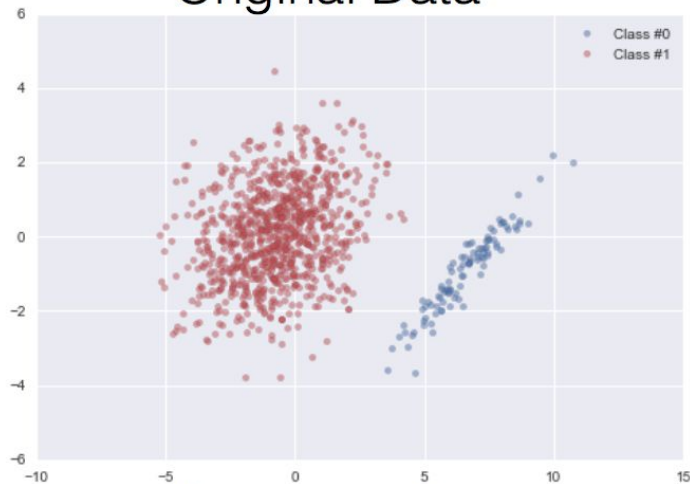
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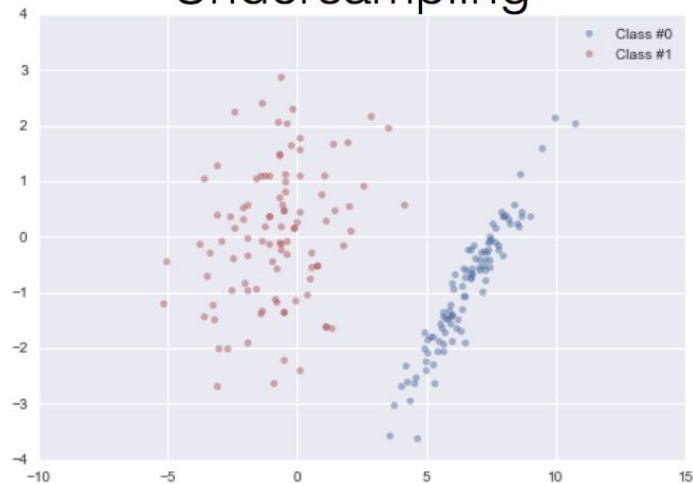
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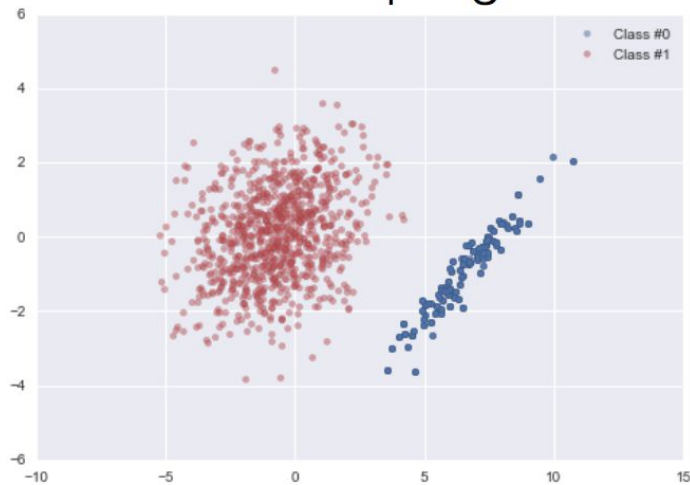
Original Data



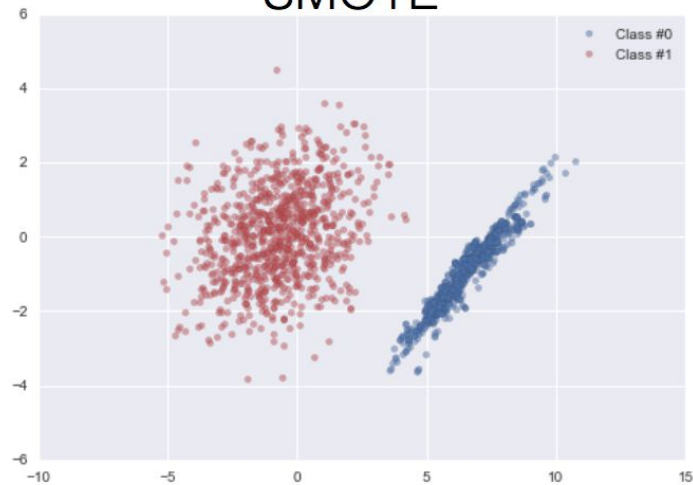
Undersampling



Oversampling



SMOTE



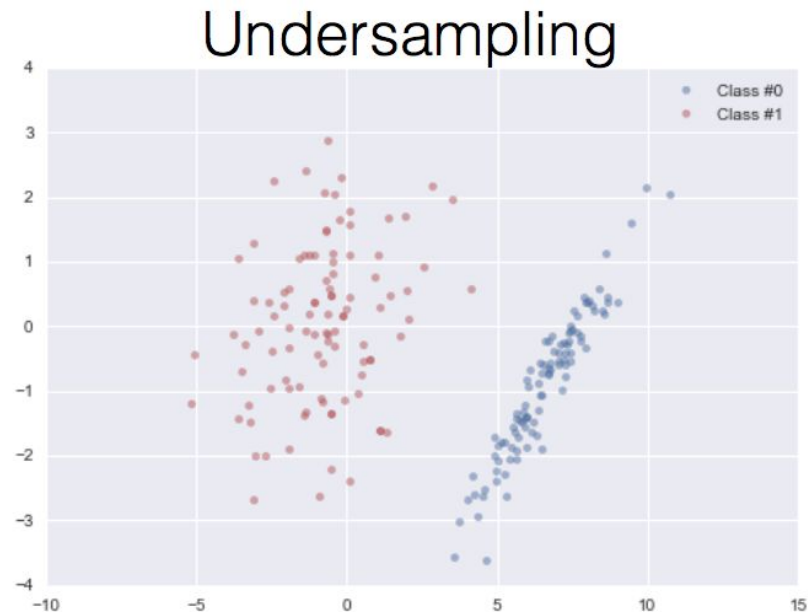
Undersampling



Undersampling randomly discards majority class observations to balance training sample.

PRO: Reduces runtime on very large datasets.

CON: Discards potentially important observations.



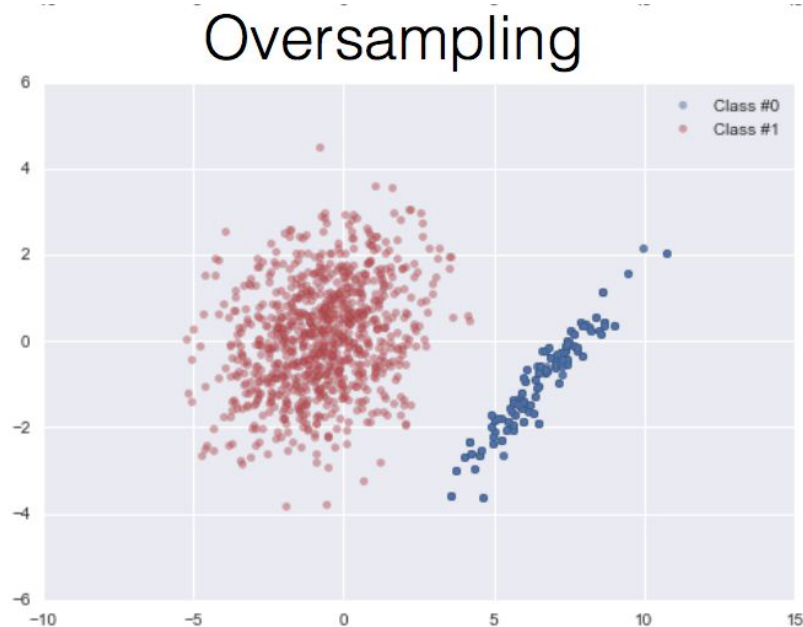
Oversampling



Oversampling replicates observations from minority class to balance training sample.

PRO: Doesn't discard information.

CON: Likely to overfit.

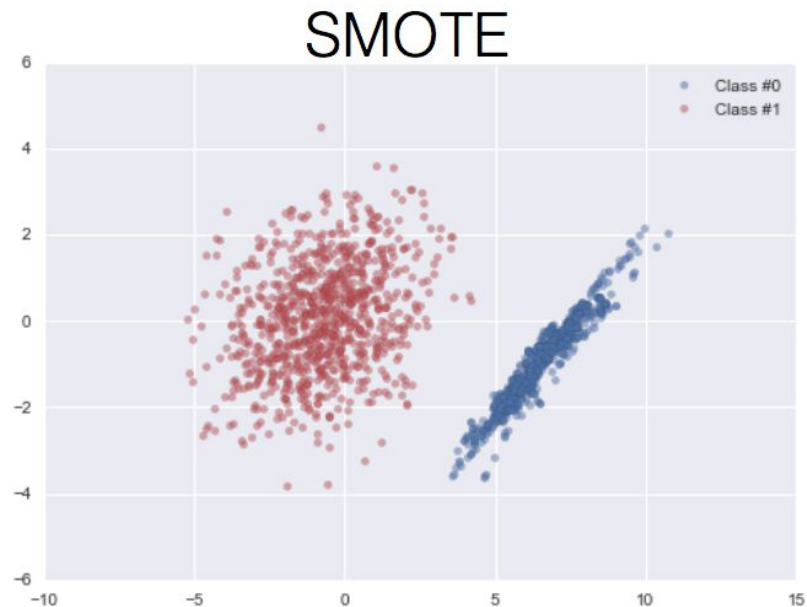


SMOTE - Synthetic Minority Oversampling TEchnique



Generates new observations from minority class.

For each minority class observation and for each feature, randomly generate between it and one of its k-nearest neighbors.



SMOTE pseudocode



```
synthetic_observations = []  
while len(synthetic_observations) + len(minority_observations) < target:  
    obs = random.choice(minority_observations):  
    neighbor = random.choice(kNN(obs, k)) # randomly selected neighbor  
    new_observation = {}  
    for feature in obs:  
        weight = random() # random float between 0 and 1  
        new_feature_value = weight*obs[feature] \  
                               + (1-weight)*neighbor[feature]  
        new_observation[feature] = new_feature_value  
    synthetic_observations.append(new_observation)
```

Consider these 3 scenarios:

- 1) You are building a model to determine if credit card charges are **fraudulent**.
You have the data for **10,000** credit card charges and **100** of them are fraudulent.
- 2) You are building to model to determine if a picture is of **a dog or a cat**.
You have **40,000** pictures of dogs and **10,000** pictures of cats.
- 3) You are building a model to **detect spam emails**.
You have **1,000,000** emails and **25,000** of the emails are spam.

In each of these scenarios,

- What percent of the data points is the minority class?
- What should you do in each of these scenarios?
Would you use any of SMOTE, undersampling or oversampling?
- What questions might you want to ask about your data to help facilitate determining the answer?



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