

How can we know that a machine learning algorithm classifies and detects faults well?

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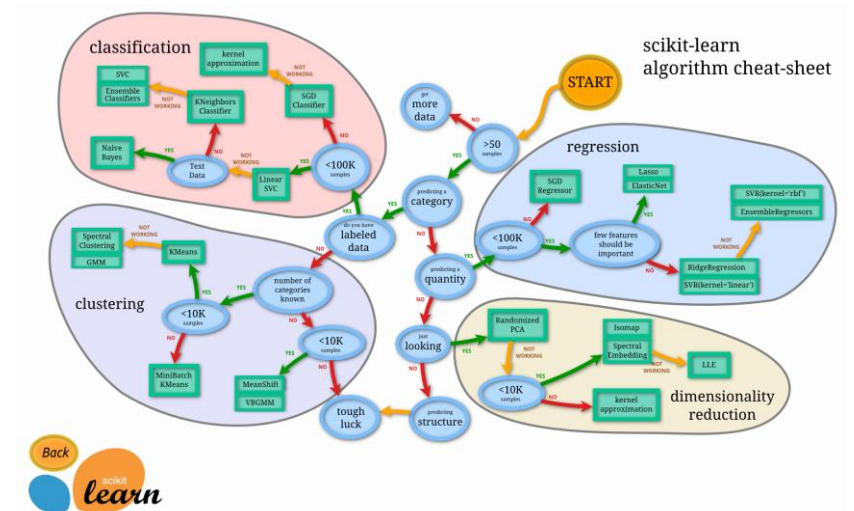
2018/10/25

Agenda

- Classification: what can we do with it?
- What is a good classification algorithm?
 - Confusion matrix and Accuracy score
 - True and False Positive Rate
 - Receiver Operating Characteristic Curve
- Example on complex applications
- Conclusions

Classification

- One major application of supervised learning methods in machine learning
- Work on categorized training data
 - Learn how categories vary with data
 - Categorize future data automatically



Classification

- Applications
 - Prediction of future event outcome

Exam 1 grade	Quiz 1 grade	Course grade
80	50	Yes
50	70	No

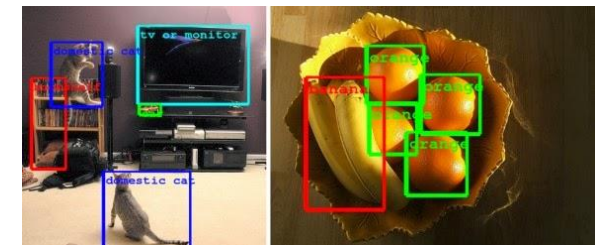
Exam 1 grade	Quiz 1 grade	Course grade
50	20	?
60	30	?

- Fault detection and diagnostics



Normal?
Stator fault?
Rotor fault?

- Image recognition



Classification

- Example algorithms
 - Logistic Regression Classification
 - Support Vector Classification
 - Naïve Bayes Classification
- Their end products are similar
 - Predicted categories
 - Hence similar evaluation method

Good classification algorithm

- Predict the classes correctly
- Consider the confusion matrix of the training data

	Class 1 data	Class 2 data	Class 3 data
Predicted to be class 1	50	30	10
Predicted to be class 2	10	60	5
Predicted to be class 3	20	10	80

- More counts on the diagonal, more accurate a classification is

But is that how
it should be?

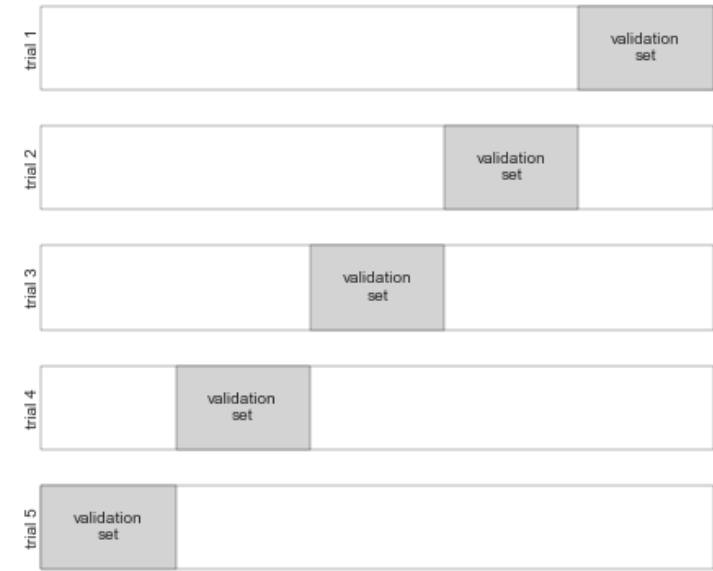
- There are quite a few problems in the previous analysis
 - Used all training data for evaluation
 - Not simulating what will happen to cases not used for training
 - Not application specific
 - Not all classes are equal
 - On a specific setup
 - What will happen if the user wants a set of stricter/ more relaxed rules?

How can we
address the
issues?

- Cross-validation
- True and false positive rates
- Receiver-operating characteristic (ROC) curve

Cross-validation

- Separate training datasets into multiple subsets
- Get accuracy scores of all trials with their own validation sets
- Examine the performance of the algorithms in cases outside their training data



VanderPlas (2016)

True and false positive rates

- Not all classes are equal!
- Example: Fault Detection and Diagnostics
 - Sometimes classification algorithms are only used to evaluate if a minor issue occurs
 - Send someone to repair the issue if a fault happens
 - But sending someone to fix some non-existing issues are costly
 - Worse than sending no one at all!
- You want to check the accuracy of the classes differently

True and false positive rates

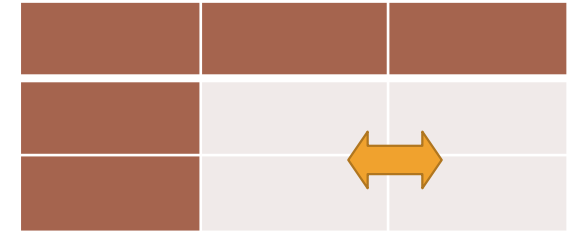
- Consider a confusion matrix

	Predicted to be class 1	Predicted to be other classes
Really belongs to class 1	True positive	False negative
It's not in class 1	False positive	True negative

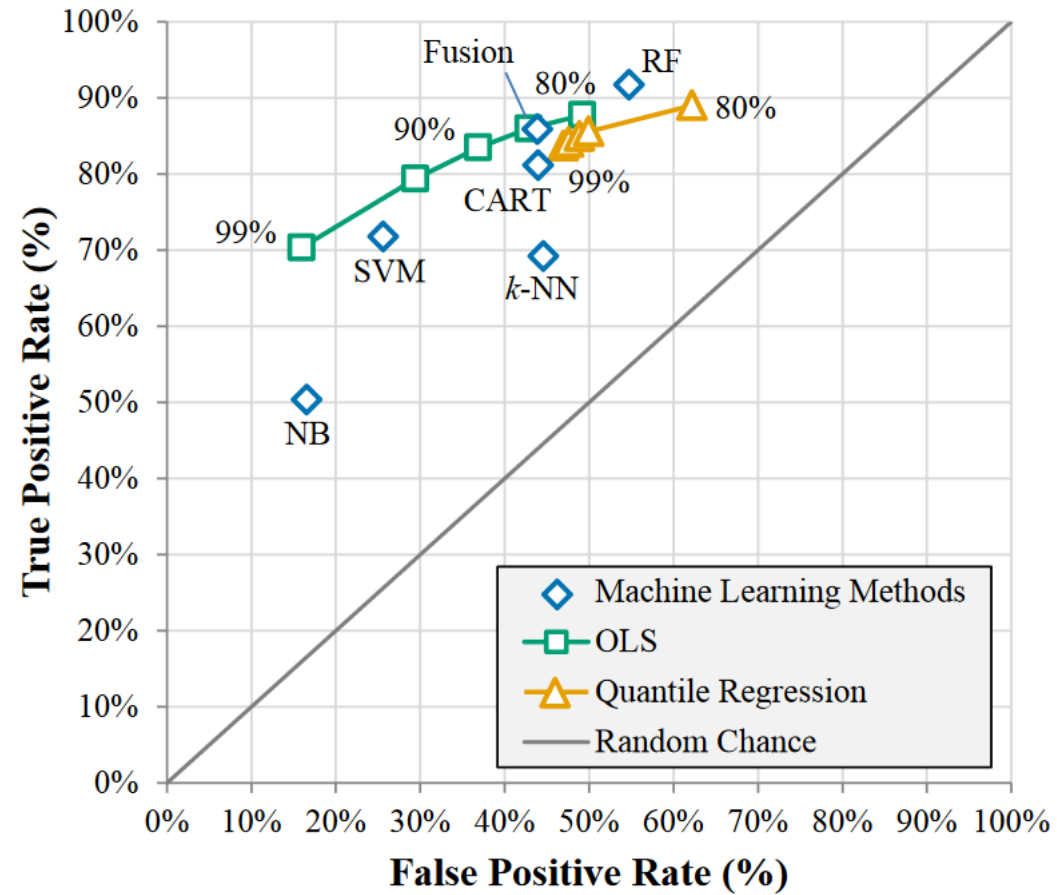
- If a class 1 prediction requires costly actions, you will need a algorithm
 - Very low false positive rate $= \frac{\text{Number of false positive cases}}{\text{Number of non-class 1 cases}}$
 - Moderately high true positive rate $= \frac{\text{Number of true positive cases}}{\text{Number of actual class 1 cases}}$

Receiver operating characteristic curves

- There are thresholds to adjust the criteria between the boundaries of the classes
 - Regularization strength to avoid overfitting at the cost of accuracy
 - Confidence level
- Change of threshold changes the performance of the algorithm
- Range of performance metrics instead of just one metric



ROC curve



Frank et al. (2016)

Study of a problematic case

- There are some algorithms trying to claim very different classification rules to game the system
- Claim: “Our algorithm is not so good at the identification of Issues Y and Z. If Issue Y exists, it may raise either Issue Y or Z alarm. But not vice versa.”
- Will that work better?

Let's look at the original confusion matrices without the claim

- Since we have two diagnoses for two issues, we have two matrices
- Matrix for issue Y prediction
 - Where are the true positives for issue Y classification?
 - 4 True positives and 4 False positives

		Predicted to have both Y and Z	Predicted to have Y but not Z	Predicted to have Z but not Y	Predicted not to have Y and Z
With issue Y	With issue Z	True positive (TP)		False negative (FN)	
	Without issue Z				
Without issue Y	With issue Z	False positive (FP)		True negative (TN)	
	Without issue Z				

Let's look at the original confusion matrices without the claim

- Matrix for issue Z prediction
 - Where are the true positives for issue Z classification?
 - 4 TPs and 4 FPs

		Predicted to have both Y and Z	Predicted to have Y but not Z	Predicted to have Z but not Y	Predicted not to have Y and Z
With issue Y	With issue Z	TP	FN	TP	FN
	Without issue Z	FP	TN	FP	TN
Without issue Y	With issue Z	TP	FN	TP	FN
	Without issue Z	FP	TN	FP	TN

Let's see what will happen with the claim to the issue Z classification

- Matrix for issue Z prediction
 - WP stands for weak positive which means that the classification is partially correct

		Predicted to have both Y and Z	Predicted to have Y but not Z	Predicted to have Z but not Y	Predicted not to have Y and Z
With issue Y	With issue Z	TP	FN	<u>WP</u>	FN
	Without issue Z	FP	TN	<u>WP</u>	<u>FN</u>
Without issue Y	With issue Z	TP	FN	TP	FN
	Without issue Z	FP	TN	FP	TN

Why?

- If there are two issues but the algorithm is giving me one alarm, I am going to check for one issue only
 - One partially correct answer (WP)
- If the algorithm tells me that an issue Z exists but not issue Y, I am going to check issue Z first. If it doesn't exist, I go to check issue Y. This is not automatic!
 - Another partially correct answer (WP)
- You should give an issue Z prediction even if only issue Y exists
 - One TN turns into a FN

So what
happened?

- Convert
 - One True Positive scenario
 - One False Positive scenario
 - One True Negative scenario
- To
 - Two Weak Positive scenarios
 - One False Negative scenario
- Reduce
 - True Positive Rate, False Positive Rate and Accuracy Score
 - Only good if your false positive rate is too high

Summary

- Classification algorithm evaluation methods
 - General
 - Accuracy score and confusion matrix
 - Specific applications
 - True and false positive rates
 - Tuneable parameters
 - ROC curve
- Confusion matrix construction to evaluate special claims

References

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Evaluation

- <https://bit.ly/2SbvtiX>

QUESTIONS

RESPONSES

Evaluation of PyData Hong Kong Meetup on 2018/10/25

Form description

What do you want to learn from the event? *

- ☐ Coding skills
- ☐ Useful mathematics/ programming/ machine learning tools
- ☐ New technological applications
- ☐ Review of your own skills

