

MLADS

MACHINE LEARNING, AI,
AND DATA SCIENCE CONFERENCE

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Generalization, Utility, and Experimentation: ML Concepts for Making Better Business Decisions: Section 2: Automating Decisions

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Session goals

- 1. Learn how machine learning (ML) differs from traditional software engineering
- 2. See how ML fits in the context of **making better business decisions**
- 3. Understand why causal relationships matter in data analysis, and why we still need to do experiments

Using classifiers in business decisions

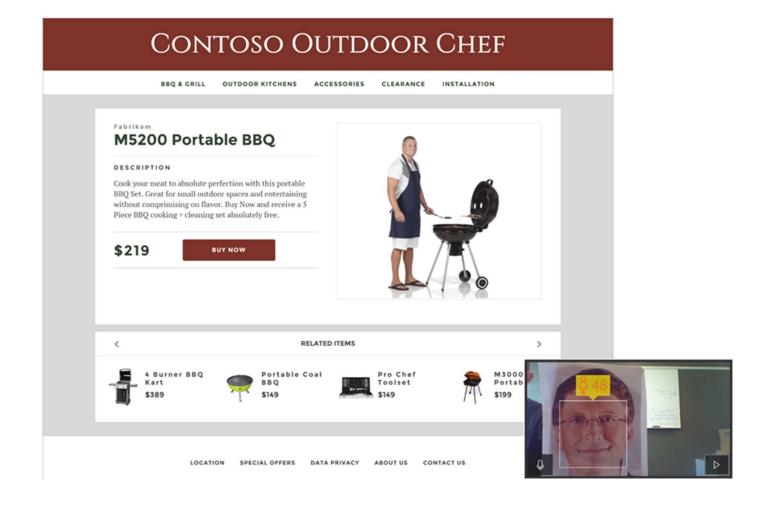
- You already make mistakes
- ML models make mistakes too
 - Can ML help you make fewer or less expensive mistakes?

- Economic Utility of a Binary Classifier
 - How much do we gain by correctly identifying positive and negative cases?
 - How much does each type of mistake cost us?

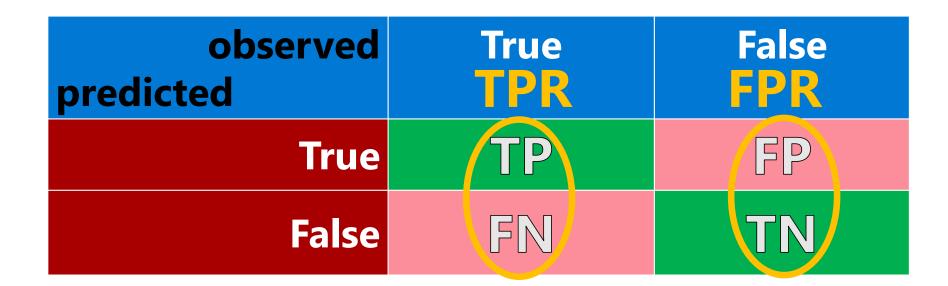




Mall Kiosk



Confusion Matrix



		True condition				
	Total population	Condition positive	Condition negative	Prevalence = $\frac{\Sigma \text{ Condition positive}}{\Sigma \text{ Total population}}$	Accuracy (ACC) = $\frac{\Sigma \text{ True positive} + \Sigma \text{ True negative}}{\Sigma \text{ Total population}}$	
Predicted condition	Predicted condition positive	True positive	False positive, Type I error	Positive predictive value (PPV), Precision = Σ True positive Σ Predicted condition positive	False discovery rate (FDR) = $\frac{\Sigma \text{ False positive}}{\Sigma \text{ Predicted condition positive}}$	
	Predicted condition negative	False negative, Type II error	True negative	False omission rate (FOR) =	Negative predictive value (NPV) = $\frac{\Sigma \text{ True negative}}{\Sigma \text{ Predicted condition negative}}$	
		True positive rate (TPR), Recall, Sensitivity, probability of detection, Power = $\frac{\Sigma \text{ True positive}}{\Sigma \text{ Condition positive}}$	False positive rate (FPR), Fall-out, probability of false alarm $= \frac{\Sigma \text{ False positive}}{\Sigma \text{ Condition negative}}$	Positive likelihood ratio (LR+) = $\frac{TPR}{FPR}$	Diagnostic odds ratio $(DOR) = \frac{LR+}{LR-}$	F ₁ score = 2 · Precision · Recall Precision + Recall
		False negative rate (FNR), Miss rate $= \frac{\Sigma \text{ False negative}}{\Sigma \text{ Condition positive}}$	Specificity (SPC), Selectivity, True negative rate (TNR) $= \frac{\Sigma \text{ True negative}}{\Sigma \text{ Condition negative}}$	Negative likelihood ratio (LR-) = $\frac{FNR}{TNR}$		

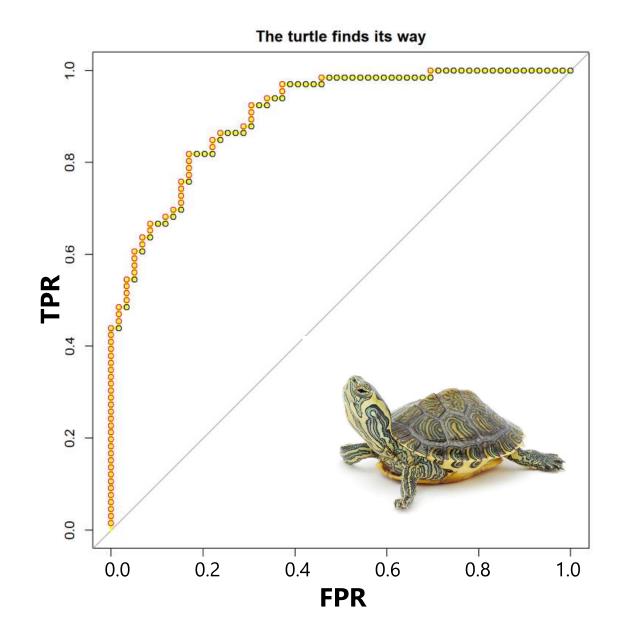
https://en.wikipedia.org/wiki/Confusion_matrix

ROC Curve:

- sort test cases by their score from the model
- march along the sequence, stepping up for positives and right for negatives

This is the same as scanning across possible cutoff threshold values.

The slope of the curve shows the concentration of positives.



Linear Utility Model

```
(TP_value * N * tpr * P) +  # sold
(FP_value * N * fpr * (1 - P)) +  # refunded
(TN_value * N * (1 - fpr) * (1 - P)) + # trashed
(FN_value * N * (1 - tpr) * P)  # wasted
```

N: number of units

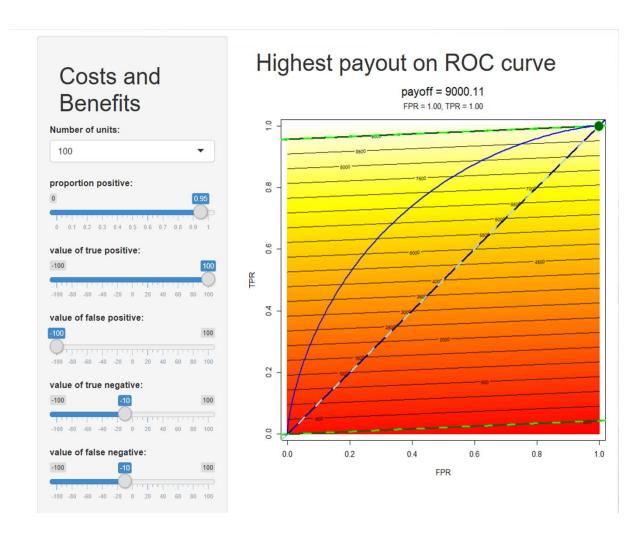
P: overall proportion positive

TP_value, FP_value, TN_value, FN_value: values (or costs) assigned to TP, FP, TN and FN cases

¹¹tpr, fpr: true positive and false positive rates

Economic Utility in ROC Space

The settings on the left are used to compute the "payoff" value of every point on the plane of true positive rate (TPR) vs. false positive rate (FPR); this is used to color the background. The parallel black lines are "lines of indifference", showing contours on the cost surface (since this cost model is linear, these are parallel lines). The ROC curve is shown in blue, and the green spot shows the point on the curve with the highest payoff. In this case the highest payoff is at [1.0, 1.0], where all cases are considered positive, and the classifier is not useful.



https://ml4managers.shinyapps.io/ROC_utility/

Resources

- Github repo: https://github.com/microsoft/datascience4managers
- · Shiny Apps:
 - https://ml4managers.shinyapps.io/ROC_utility/
 - https://ml4managers.shinyapps.io/effects of x and z/
- Economic Utility Functions Meet ROC Curves: Deciding on a Cutoff Threshold for Binary Classification. Siddarth Ramesh and Robert Horton, MLADS November 14, 2018. https://resnet.microsoft.com/video/4248
 - https://github.com/Azure/utility_functions_in_ROC_space
 - https://ml4managers.shinyapps.io/ROC_utility/

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Overloaded Terms in Data Science

model

- Statistics: (data model) a description of a system using mathematical concepts and language (with statistical assumptions about sample generation.)
- ML: (algorithmic model) data generation is a black box; the algorithm is about how to find correlations between features and outcomes.

inference

- *Statistics*: 'the process of using data analysis to deduce properties of an underlying probability distribution' (to infer properties of the population). (<u>Wikipedia</u>)
- ML: scoring or classifying new cases

experiment

- Statistics: measuring the state or value of a dependent variable when an independent variable is perturbed under controlled conditions in order to establish a cause and effect relationship.
- ML: Try a bunch of algorithms, hyperparameter settings, etc. to see how they affect performance.

regression

- English: 'a return to a former or less developed state.'
- Statistics: (regression toward the mean).
- ML: prediction of a continuous-valued outcome. Contrasted with classification.