ORES Custom Documentation V

Disclaimer: No guarantee for the correctness of information / explanations / sources is given.

Goals

1. Metric list:
   - Add examples to each metric (if possible)
   - Adjust the description of counts → labels, predictions
2. Research what form of revision data is needed (for existing visualizations, but also in general) → also check RecentChanges and new Filters and what API calls look like in that context
3. Watch "ROC curves and Area Under the Curve explained" and think about what parameters could be used in which ways to filter the output of the current UI (currently: X inputs → X outputs)

   Also check out: Precision-Recall AUC vs ROC AUC discussion
4. Read A Review of User Interface Design for Interactive Machine Learning (carefully!)
5. Think about what could be the goal of this thesis

1 Crucial metrics: damaging-model

Metrics simple list:

!f1	✓
!precision	✓
!recall	✓
accuracy	✓
counts	✓
f1	✓
filter_rate	✓
fpr	✓
match_rate	✓
pr_auc	✓
precision	✓
rates	✓
recall	✓
roc_auc	✓

The metrics are the same for the damaging and itemquality models, but a few changes will be made to the explanatory parts nontheless (compared to the version in oresDoc3). Also the structure of explanations will be changed once again (compared to the version in oresDoc4) to the following:

For each metric (if possible) there will be:

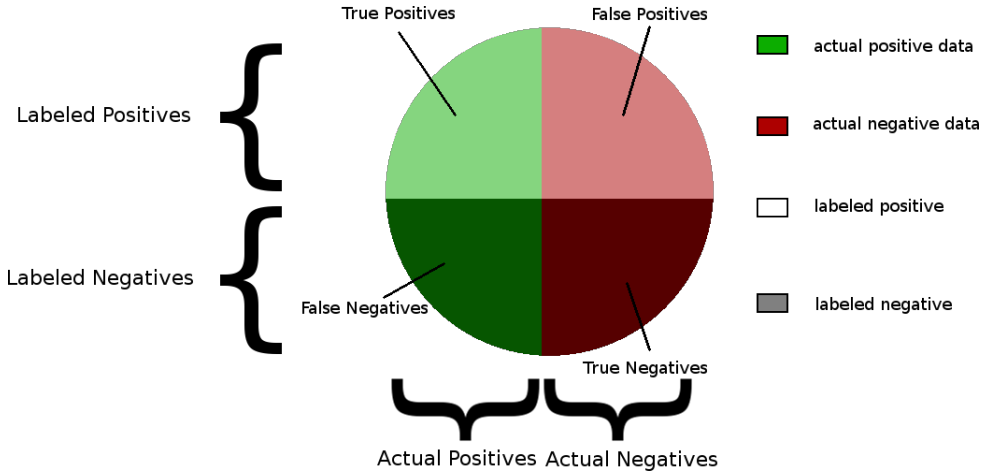
1. A definition
2. An intuitive explanation with an example
3. The formula based on the **confusion matrix**
4. Its meaning based on the "**confusion circle**"
5. Its meaning based on the **loan threshold** representation by Google (Link)

Explanations: References

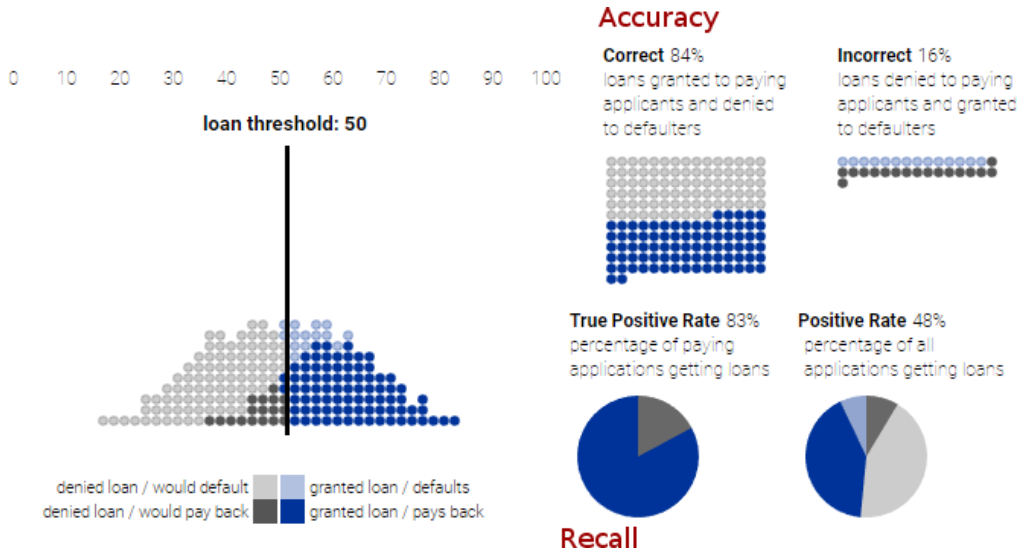
- Confusion Matrix

		Actual	
		Positive	Negative
Predicted	Positive	True Positive	False Positive
	Negative	False Negative	True Negative

- "Confusion Circle"



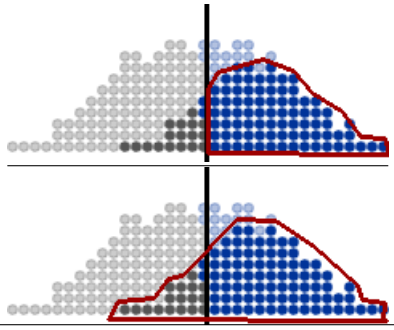
- Loan Threshold



1.1 recall

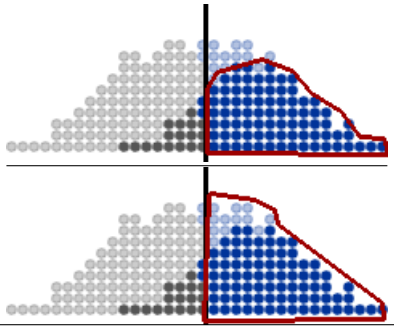
1. Recall (≡ true positive rate ≡ "sensitivity") is defined as the ability of a model to find all relevant cases within the dataset.

2. Let's consider the follow example:

2.	3.	4.
$= \frac{TP}{TP+FN}$	$=$ 	$=$ 

1.2 precision

1. Ability of the model to find only relevant cases within the dataset

2.	3.	4.
$= \frac{TP}{TP+FP}$	$=$ 	$=$ 

1.3 f1

1. F1-Score, the harmonic mean of recall and precision, a metric from 0 (worst) to 1 (best), used to evaluate the accuracy of a model by taking recall and precision into account

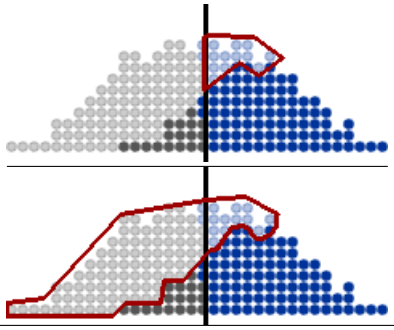
2.	3.	4.
-	-	-

$$= 2 * \frac{precision * recall}{precision + recall}$$

Compared to the simple average (of recall and precision), the harmonic mean punishes extreme values (e.g. precision 1.0 and recall 0.0 → average 0.5, but F1 = 0)

1.4 fpr

1. The false positive rate (**FPR**) is the probability of a false alarm

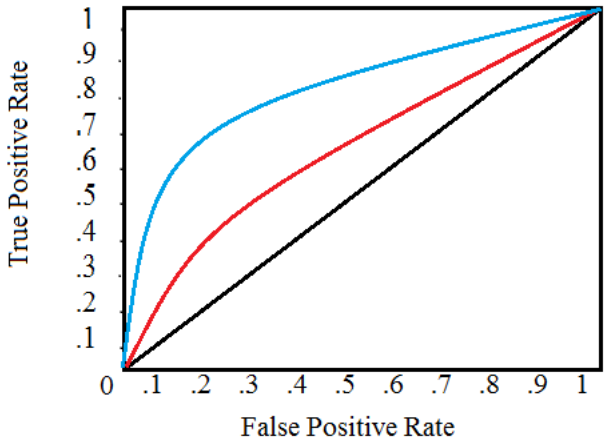
2.	3.	4.
$= \frac{FP}{FP+TN}$	$=$ 	$=$ 

1.5 roc_auc

1. The **area under** the **curve** of the **ROC**-curve, a measure between 0.5 (worthless) and 1.0 (perfect: getting no FPs), rates the ability of a model to achieve a blend of recall and precision

2.	3.	4.
-	-	-

The receiver operating characteristic (ROC) curve plots the TPR versus FPR as a function of the model's threshold for classifying a positive



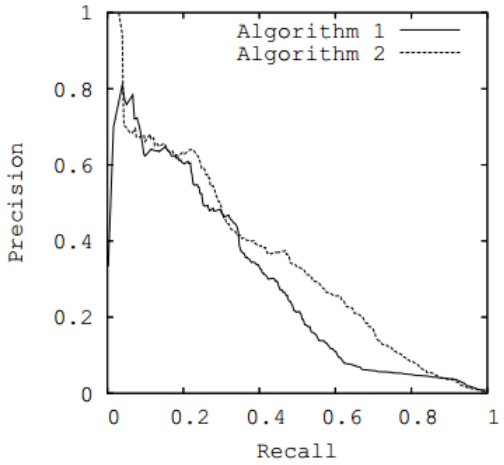
Increasing the threshold → moving up a curve (≡ model) to the top right corner, where all data is predicted as positive (threshold = 1.0) and vice versa

1.6 pr_auc

(see: link 1 and link 2)

1. The **area under** the **curve** of the **PR**-curve, same: similar objective as the **roc_auc**, but PR curves are better than ROC curves if the populations are imbalanced

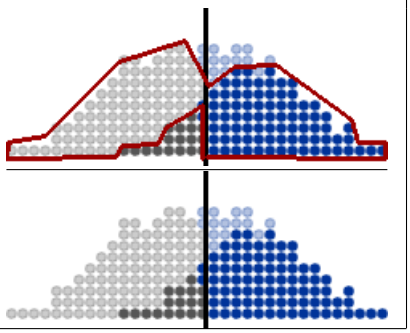
The PR-curve plots the Precision versus the Recall



Instead of the top left corner for the ROC-curve, here, we want to be in the top right corner for our classifier to be perfect

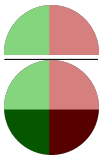
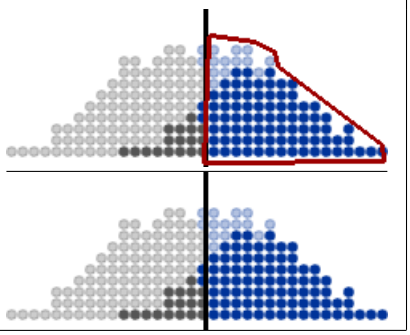
1.7 accuracy

1. Measuring the portion of correctly predicted data

2.	3.	4.
$= \frac{\texttt{TP+TN}}{\texttt{Total}}$	$=$ 	$=$ 

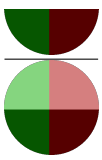
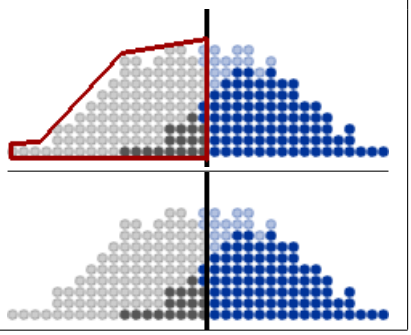
1.8 match_rate

1. The proportion of observations matched/not-matched

2.	3.	4.
$= \frac{\texttt{TP+FP}}{\texttt{Total}}$	$=$ 	$=$ 

1.9 filter_rate

1. The proportion of observations filtered/not-filtered

2.	3.	4.
$= 1 - \texttt{match\_rate} = \frac{\texttt{TN+FN}}{\texttt{Total}}$	$=$ 	$=$ 

1.10 counts

1. The number of edits labeled as *false* and *true*

2.	3.	4.
-	-	-

When calling the enwiki damaging model for example (Link), you'll notice the following under counts:


```
"counts": {
  "labels": {
    "false": 18677,
    "true": 751
  },
  "n": 19428,
  "predictions": {
    "false": {
      "false": 17958,
      "true": 719
    },
    "true": {
      "false": 320,
      "true": 431
    }
  }
},
```


The information stored in *labels* is what we defined above under **1.**

n is the total number of edits taken into account

predictions is where it gets interesting: *false* and *true* as parents of another two of those are the labels and the values of their "child"-booleans are the actual values of their edits

⇒ e.g. of 18677 edits that were labeled as *false*, 719 were false negatives

1.11 rates

1. The rates simply equal $\frac{\texttt{label}}{\texttt{n}}$, both from **counts** for *rates*: *sample*: *label*, and with *label* = *false* or *true*

   So *rates*: *sample*: *false*: 0.961 = $\frac{18677}{19428}$

2.	3.	4.
-	-	-

Calling the API the same way as for **counts**, we get:


```
"rates": {
  "population": {
    "false": 0.966,
    "true": 0.034
  },
  "sample": {
    "false": 0.961,
    "true": 0.039
  }
},
```


As already mentioned, the size of *sample* equals our n in **counts** = 19428.

But why have a sample and the whole population? Because there is a significant number of bot edits and edits that don't need reviewing (admins, autopatrolled users). The sample of edits does not contain any of those.

1.12 !<metric>

- Any <metric> with an exclamation mark is the same metric for the negative class
- e.g. recall = $\frac{\texttt{TP}}{\texttt{TP+FN}} \Rightarrow$ **!**recall = $\frac{\texttt{TN}}{\texttt{TN+FP}}$
- Example usage: find all items that are not "E" class → look at **!**recall for "E" class.

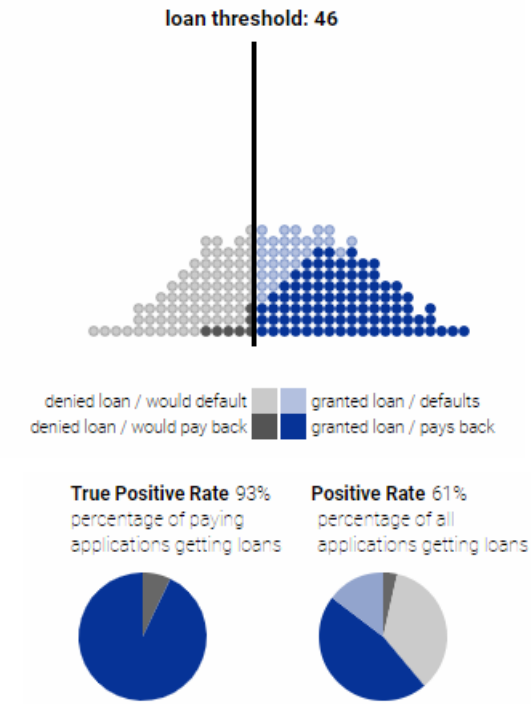
1.12.1 Existing !<metric>s

- !f1
- !precision
- !recall

1.13 Additional explanations

1.13.1 recall vs precision

When increasing one of these two, the other one naturally decreases. For an intuitive example, let's take a look at Google's Loan Threshold Simulation:



The dark grey / dark blue dots, representing clients that would actually pay back their loan, are more and more included ($\rightarrow$ given loans) if we move the threshold further to the left.

But so are clients that would not. Thus moving the threshold to the left increases the **recall** (**tpr**) but decreases the **precision** and vice versa when moving to the right.

1.13.2 roc_auc vs pr_auc

see: `https://www.kaggle.com/general/7517`

- tl;dr: if the class imbalance problem exists, **pr_auc** is more appropriate than **roc_auc**

  If TNs are not meaningful to the problem or there are a lot more negatives than positives, **pr_auc** is the way to go (it does not account for TNs).

- In other words:

  – If the model needs to perform equally on the positive and negative class $\rightarrow$ **roc_auc**

  - If it's not interesting how the model performs on negative class → **pr_auc** (example: detecting cancer; find all positives and make sure they're correct!)

Questions

- Q: Should I ask Aaron how he would like us to work together? I'm not sure how he meant it.

  A:

- Q: In what situations exactly do we want to optimize the threshold in the context of user centered threshold optimization?

  A: