Mudcard questions

- **If I have a high imbalanced data of some features, but it is a regression problem, which evaluation metrics should I use?**
  - only the classification target variable can be imbalanced, it generally does not matter if a categorical feature is imbalanced
  - select from any of the regression metrics we will cover today
- **The fbeta score seems muddiest to me - why would we have to square beta to get the relative weight of precision and recall.**
- **Why is the harmonic mean used for the F score?**
  - that's the equation of a weighted harmonic mean
  - there are other means you can use to combine P and R but the weighted harmonic mean has a nice property that other means do not have:
    - if either P or R are 0, the weighted harmonic mean is 0 too
    - this is not the case for the simple mean for example
- **why we should use a large beta when it's cheap to act?**
  - if beta is large, it will give more weight to recall
  - recall measure what fraction of the condition positives are correctly identified
  - if it's cheap to act and it's not too bad if you act on incorrectly classified points (e.g., send propomtional emails), recall is what you care about most
- **I am a little confused about expensive and cheap act.**
  - you develop ML models to make predictions and more importantly **to act on those predictions**
    - predict stocks price: should i buy or sell certain stocks?
    - predict cancer: should this patient receive chemotherapy?
    - predict loan defaults: should we give lona to this person or not?
    - predict engagement/shopping: should i send a propmotional email to this person or not?
    - predict if user will click on ad: should i show this ad to the person or not?
  - interventions carry certain risks
    - expensive to act: treating a patient who has no cancer with chemotherapy is a very bad idea
      - making a mistake is costly because chemo is tough and has a ton of sideeffects
    - cheap to act: sending an email to a customer is no big deal even if they won't shop
      - the mistake is not costly because an extra email in someone's mailbox is no big deal
- **I'm a little confused about the normalization part in the plot_confusion_matrix function.**
- **if I apply normalization to confusion matrix, how that going to effect the result?**
  - there are several ways to normalize the confusion matrix
  - the plot_confusion_matrix function normalizes along the true class 0/1 rows so the values of each row will sum to 1 while the values of each column won't

        - you could also normalize the whole confusion matrix such that all values sum to 1
        - you could also normalize such that the predicted class0/1 columns sum to 1 but this is rarely done
- **still confused about how to choose a metric**
    - always consider how you will act based on the model's prediction
    - weight how bad it is to act on a false positive and how bad it is to not act on a false negative
- **How do you come to a final decision on what B should be? I understand that B effects accuracy and precision, and you can change B to effect the scores of each, but how do you decide to what degree you change B?**
    - see answers above
    - how will you act based on your model's prediction?
    - weight the effect of incorrect action on false positives and false neagtives

Evaluation metrics in supervised ML, part 2, predicted probabilities and regression metrics

By the end of this lecture, you will be able to

- Summarize the ROC and precision-recall curves, and the logloss metric
- Describe the most commonly used regression metrics

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The ROC curve

- Receiver Operating Characteristic
    - x axis: false positive rate (fpr = FP / (FP + TN))
    - y axis: true positive rate (R = TP / (TP + FN))
    - the curve shows fpr and R value pairs for various class 1 critical probabilities
- upper left corner: perfect predictor
- diagonal point: chance level predictions
- lower right corner: worst predictor

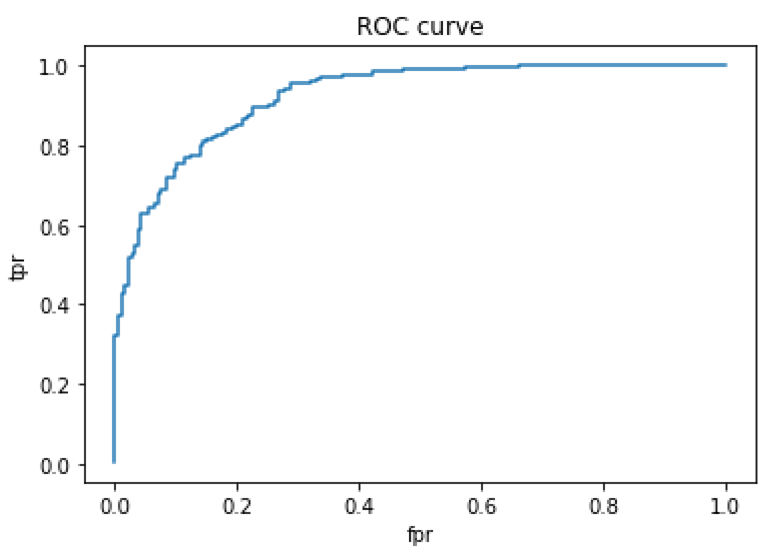
In [1]:

```
import pandas as pd
import matplotlib.pyplot as plt
import numpy as np
from sklearn.metrics import confusion_matrix
df = pd.read_csv('data/true_labels_pred_probs.csv')

y_true = df['y_true']
```

```python
pred_prob_class1 = df['pred_prob_class1']

fpr = np.zeros(len(y_true))
tpr = np.zeros(len(y_true))

p_crits = np.sort(pred_prob_class1) # the sorted predicted probabilities serve a

for i in range(len(p_crits)):
    p_crit = p_crits[i]

    y_pred = np.zeros(len(y_true))
    y_pred[pred_prob_class1 < p_crit] = 0
    y_pred[pred_prob_class1 >= p_crit] = 1

    C = confusion_matrix(y_true,y_pred)

    tpr[i] = C[1,1]/(C[1,0]+C[1,1])
    fpr[i] = C[0,1]/(C[0,0]+C[0,1])

# from sklearn.metrics import roc_curve
# # the roc_curve function performs the same calculation
# fpr,tpr,p_crits = roc_curve(y_true,pred_prob_class1)
```

In [2]:

```python
plt.plot(fpr,tpr)
plt.xlabel('fpr')
plt.ylabel('tpr')
plt.title('ROC curve')
plt.show()
```



Quiz 1

What's the (fpr,tpr) coordinate on the ROC curve if p_crit = 1?

ROC AUC

- ROC is useful but it is not a single number metric
    - it cannot be directly used to compare various classification models

- summary statistics based on the ROC curve (for a complete list, see here)
- most commonly used metric is ROC AUC - ROC Area Under the Curve
  - AUC = 1 is a perfect classifier
  - AUC > 0.5 is above chance-level predictor
  - AUC = 0.5 is a chance-level classifier
  - AUC < 0.5 is a bad predictor
  - AUC = 0 classifies all points incorrectly

In [4]:

```
from sklearn.metrics import roc_auc_score
print(roc_auc_score(y_true,pred_prob_class1))
```

```
0.9236524315231854
```

Precision-recall curve

- the drawback of ROC is that it uses TN, not good for imbalanced problems.
- the precision-recall curve doesn't use TN, ideal for imbalanced problems.

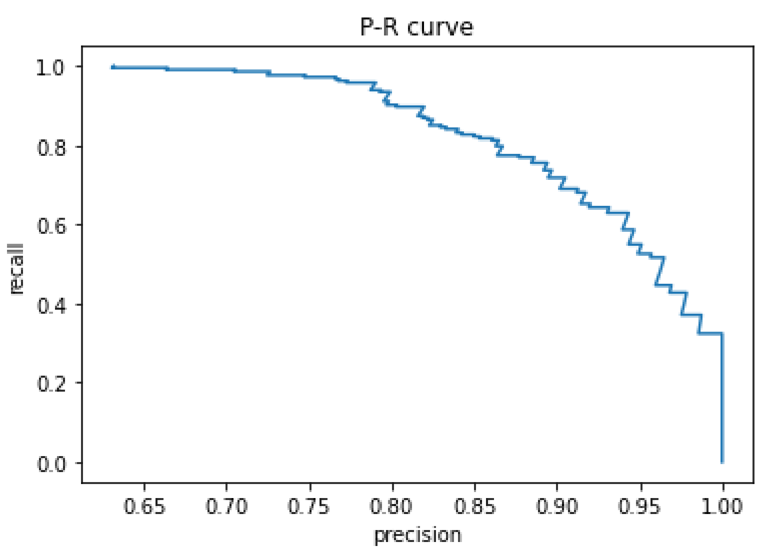
In [5]:

```
from sklearn.metrics import precision_recall_curve
from sklearn.metrics import average_precision_score # the AUC of the P-R curve

p,r,p_crits = precision_recall_curve(y_true,pred_prob_class1)

print(average_precision_score(y_true,pred_prob_class1))
```

```
0.9315588971251673
```

In [6]:

```
plt.plot(p,r)
plt.xlabel('precision')
plt.ylabel('recall')
plt.title('P-R curve')
plt.show()
```



Quiz 2

What's the (p,r) coordinate on the curve if p_crit = 0?

The logloss metric

$$logloss = -\frac{1}{N}\sum(y_{true}\ln(p_{pred}) + (1 - y_{true})(1 - \ln(1 - p_{pred})))$$

- p_{pred} is the predicted probability of the **positive class**
- the predicted probabilities are not converted into predicted classes
- excellent choice if you need accurate probabilities (e.g., when it is expensive/costly to act due to limited resources so you need to rank your points based on probabilities)
- two scenarios:
  - y_true = 0 - left term disappears
  - y_true = 1 - right term disappears
- log(0) is undefined
  - p_{pred} is replaced with $\max(\min(p, 1 - 10^{-15}), 10^{-15})$ to avoid this issue

The extreme cases

- the classifier is confidently wrong
  - $p_{pred} = 10^{-15}$ for points in class 1
  - $p_{pred} = 1 - 10^{-15}$ for points in class 0

$$logloss = -\frac{1}{N}\sum\ln(10^{-15}) = -\ln(10^{-15})$$

$$logloss \sim 34.5$$

- the classifier is correct
  - $p_{pred} = 10^{-15}$ for points in class 0
  - $p_{pred} = 1 - 10^{-15}$ for points in class 1

$$logloss = -\frac{1}{N}\sum(1-0)(1 - \ln(1 - 10^{-15})) = 10^{-15} \text{ for class 0}$$

$$logloss = -\frac{1}{N}\sum 1 * \ln(1 - 10^{-15}) = 10^{-15} \text{ for class 1}$$

$$logloss \sim 0$$

In [8]:

```
from sklearn.metrics import log_loss
print(log_loss(y_true,pred_prob_class1))
help(log_loss)
```

```
0.35015190545328556
Help on function log_loss in module sklearn.metrics._classification:

log_loss(y_true, y_pred, *, eps=1e-15, normalize=True, sample_weight=None, label
s=None)
    Log loss, aka logistic loss or cross-entropy loss.

    This is the loss function used in (multinomial) logistic regression
    and extensions of it such as neural networks, defined as the negative
    log-likelihood of a logistic model that returns ``y_pred`` probabilities
    for its training data ``y_true``.
    The log loss is only defined for two or more labels.
```

```
For a single sample with true label yt in {0,1} and
estimated probability yp that yt = 1, the log loss is

    -log P(yt|yp) = -(yt log(yp) + (1 - yt) log(1 - yp))

Read more in the :ref:`User Guide <log_loss>`.

Parameters
----------
y_true : array-like or label indicator matrix
    Ground truth (correct) labels for n_samples samples.

y_pred : array-like of float, shape = (n_samples, n_classes) or (n_samples,)
    Predicted probabilities, as returned by a classifier's
    predict_proba method. If ``y_pred.shape = (n_samples,)``
    the probabilities provided are assumed to be that of the
    positive class. The labels in ``y_pred`` are assumed to be
    ordered alphabetically, as done by
    :class:`preprocessing.LabelBinarizer`.

eps : float
    Log loss is undefined for p=0 or p=1, so probabilities are
    clipped to max(eps, min(1 - eps, p)).

normalize : bool, optional (default=True)
    If true, return the mean loss per sample.
    Otherwise, return the sum of the per-sample losses.

sample_weight : array-like of shape (n_samples,), default=None
    Sample weights.

labels : array-like, optional (default=None)
    If not provided, labels will be inferred from y_true. If ``labels``
    is ``None`` and ``y_pred`` has shape (n_samples,) the labels are
    assumed to be binary and are inferred from ``y_true``.

    .. versionadded:: 0.18

Returns
-------
loss : float

Examples
--------
>>> from sklearn.metrics import log_loss
>>> log_loss(["spam", "ham", "ham", "spam"],
...          [[.1, .9], [.9, .1], [.8, .2], [.35, .65]])
0.21616...

References
----------
C.M. Bishop (2006). Pattern Recognition and Machine Learning. Springer,
p. 209.

Notes
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The logarithm used is the natural logarithm (base-e).
```

Evaluation metrics in supervised ML, part 2, predicted

probabilities and regression

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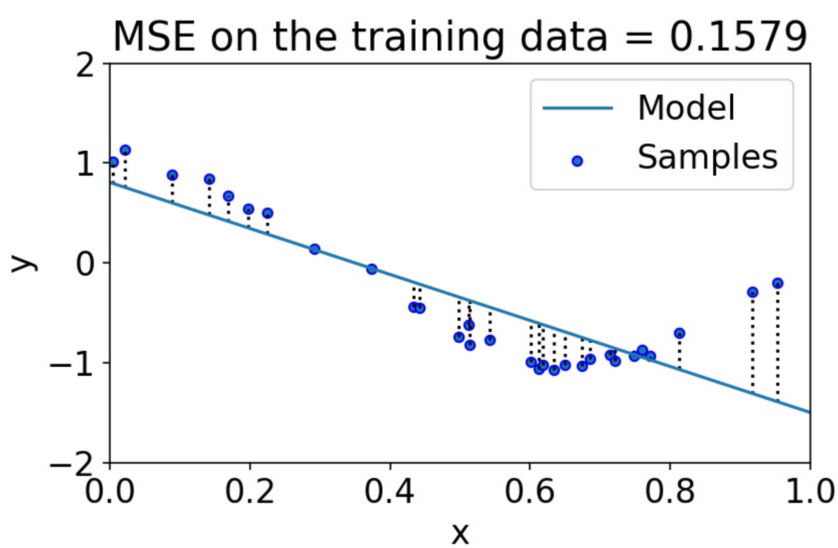
- **Describe the most commonly used regression metrics**

Regression metrics

- the target variable is continuous
- the predicted values are also continuous
- regression metrics measure some type of difference between y (true values) and y' (predicted values)

Mean Squared Error

$$MSE(y, y') = \frac{1}{n} \sum_{i=1}^{n} (y_i - y_i')^2$$



The unit of MSE is not the same as the target variable.

Root Mean Square Error

$$RMSE(y, y') = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_i - y_i')^2}$$

Mean Absolute Error

$$MAE(y, y') = \frac{1}{n} \sum_{i=1}^{n} |y_i - y_i'|$$

Both RMSE and MAE have the same unit as the target variable.

R2 score - coefficient of determination

$$R^2(y,y') = 1 - \frac{\sum_{i=1}^{n}(y_i-y_i')^2}{\sum_{i=1}^{n}(y_i-\bar{y})^2},$$

where $\bar{y}$ is the mean of y.

- R2 = 1 is the perfect regression model ($y == y'$)
- R2 = 0 is as good as a constant model that always predicts the expected value of y ($\bar{y}$)
- R2 < 0 is a bad regression model

R2 is dimensionless.

In [9]:
```
from sklearn.metrics import mean_squared_error
from sklearn.metrics import mean_absolute_error
from sklearn.metrics import r2_score
```

- RMSE is not implemented in sklearn, but you can calculate it as `np.sqrt(mean_squared_error(y_true,y_pred))`
- you can find more on regression metrics here

Quiz 3

Read in `data/reg_preds.csv` . It contains two columns:

- y_true: value of owner-occupied homes in $1000's in Boston
- y_pred: predictions of a regression model

What's the ratio between the MSE and the variance of the home values? How does this ratio relate to the R2 score?

In [ ]:
```
```

Mudcard

In [ ]:
```
```