Predicting customer churn with scikit-learn

by Eric Chiang | March 20, 2014

Customer Churn

"Churn Rate" is a business term describing the rate at which customers leave or cease paying for a product or service. It's a critical figure in many businesses, as it's often the case that acquiring *new* customers is a lot more costly than retaining *existing* ones (in some cases, 5 to 20 times more expensive).

Understanding what keeps customers engaged, therefore, is incredibly valuable, as it is a logical foundation from which to develop retention strategies and roll out operational practices aimed to keep customers from walking out the door. Consequently, there's growing interest among companies to develop better churn-detection techniques, leading many to look to data mining and machine learning for new and creative approaches.

Predicting churn is particularly important for businesses w/ subscription models such as cell phone, cable, or merchant credit card processing plans. But modeling churn has wide reaching applications in many domains. For example, casinos have used predictive models to predict ideal room conditions for keeping patrons at the blackjack table and when to reward unlucky gamblers with front row seats to Celine Dion. Similarly, airlines may offer first class upgrades to complaining customers. The list goes on.

Learn More

This is a post about modeling customer churn using Python.

Facebook

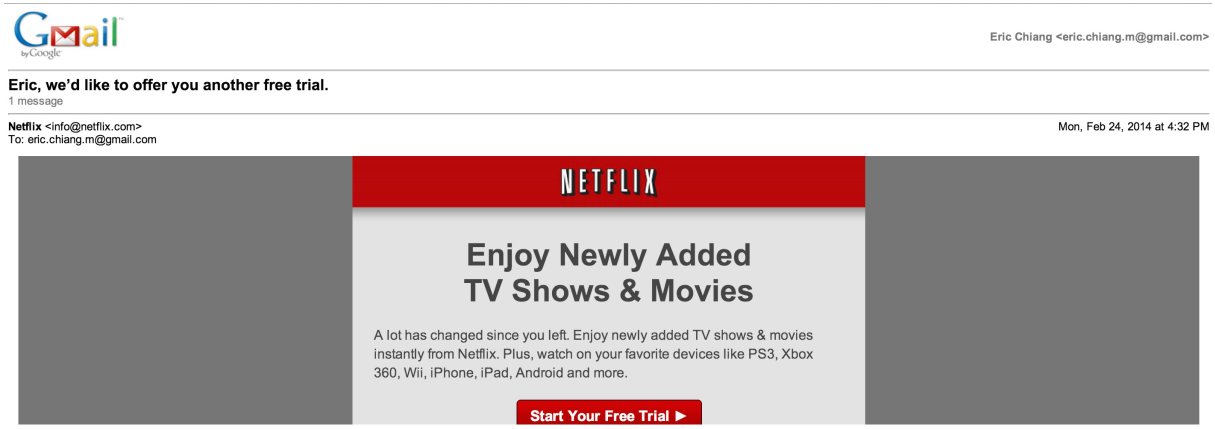
Twitter

Linkedin

Reddit

Wait, don't go!

So what are some of ops strategies that companies employ to prevent churn? Well, reducing churn, it turns out, often requires non-trivial resources. Specialized retention teams are common in many industries and exist expressly to call down lists of at-risk customers to plead for their continued business.



Gmail by Google

Eric Chiang <eric.chiang.m@gmail.com>

Eric, we'd like to offer you another free trial.
1 message

Netflix <info@netflix.com>
To: eric.chiang.m@gmail.com

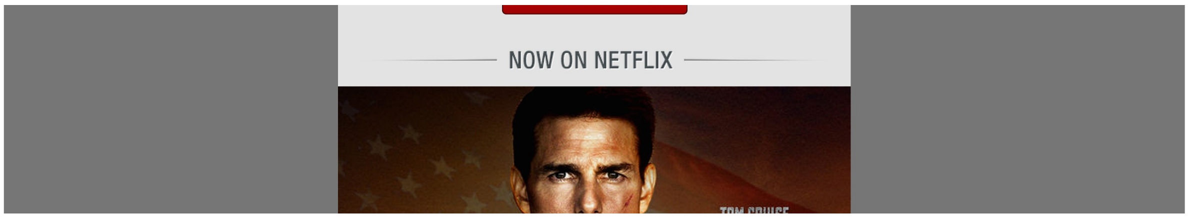
Mon, Feb 24, 2014 at 4:32 PM

NETFLIX

Enjoy Newly Added TV Shows & Movies

A lot has changed since you left. Enjoy newly added TV shows & movies instantly from Netflix. Plus, watch on your favorite devices like PS3, Xbox 360, Wii, iPhone, iPad, Android and more.

Start Your Free Trial ►



Organizing and running such teams is tough. From an ops perspective, cross-geographic teams must be well organized and trained to respond to a huge spectrum of customer complaints. Customers must be accurately targeted based on churn-risk, and retention treatments must be well-conceived and correspond reasonably to match expected customer value to ensure the economics make sense. Spending $1,000 on someone who wasn't about to leave can get expensive pretty quickly.

The good news is that we live in the data age and have some pretty great tools at our disposal to help answer these questions. John Forman of MailChimp summarizes this well:

Learn More

Facebook

Twitter

LinkedIn

Reddit

> "I work in the e-mail marketing industry for a website called MailChimp.com. We help customers send e-mail newsletters to their audience, and every time someone uses the term 'e-mail blast,' a little part of me dies.
>
> "Why? Because e-mail addresses are no longer black boxes that you lob 'blasts' at like flash grenades. No, in e-mail marketing (as with many other forms of online engagement, including tweets, Facebook posts, and Pinterest campaigns), a business receives feedback on how their audience is engaging at the individual level through click tracking, online purchases, social sharing, and so on. This data is not noise. It characterizes your audience. But to the uninitiated, it might as well be Greek. Or Esperanto."

- John Foreman, *DataSmart*

Within this frame of mind, efficiently dealing with turnover is an exercise of distinguishing who is likely to churn from who is not using the data at our disposal. The remainder of this post will explore a simple case study to show how Python and its scientific libraries can be used to predict churn and how you might deploy such a solution within operations to guide a retention team.

The Dataset

The data set I'll be using is a longstanding telecom customer data set which you can download here.

The data is straightforward. Each row represents a subscribing telephone customer. Each column contains customer attributes such as phone number, call minutes used during different times of day, charges incurred for services, lifetime account duration, and whether or not the customer is still a customer.

Learn More
Facebook
Twitter
Linkedin
Reddit

In [2]:

```
from __future__ import division
import pandas as pd
import numpy as np

churn_df = pd.read_csv('churn.csv')
col_names = churn_df.columns.tolist()

print "Column names:"
print col_names

to_show = col_names[:6] + col_names[-6:]
```

```
print "\nSample data:"
churn_df[to_show].head(6)
```

```
        Column names:
        ['State', 'Account Length', 'Area Code', 'Phone', "Int'l Plan", 'V
Mail Plan', 'VMail Message', 'Day Mins', 'Day Calls', 'Day Charge', 'Eve Min
s', 'Eve Calls', 'Eve Charge', 'Night Mins', 'Night Calls', 'Night Charge',
'Intl Mins', 'Intl Calls', 'Intl Charge', 'CustServ Calls', 'Churn?']

        Sample data:
```

Out[2]:

Learn More
Facebook
Twitter
Linkedin
Reddit

	State	Account Length	Area Code	Phone	Int'l Plan	VMail Plan	Night Charge	Intl Mins	Intl Calls	Intl Charge	CustServ Calls	Churn?
0	KS	128	415	382-4657	no	yes	11.01	10.0	3	2.70	1	False.
1	OH	107	415	371-7191	no	yes	11.45	13.7	3	3.70	1	False.
2	NJ	137	415	358-1921	no	no	7.32	12.2	5	3.29	0	False.
3	OH	84	408	375-9999	yes	no	8.86	6.6	7	1.78	2	False.
4	OK	75	415	330-6626	yes	no	8.41	10.1	3	2.73	3	False.
5	AL	118	510	391-8027	yes	no	9.18	6.3	6	1.70	0	False.

6 rows × 12 columns

I'll be keeping the statistical model pretty simple for this blog so the feature space is almost unchanged from what you see above. The following code simply drops irrelevant columns and converts strings to boolean values (since models don't handle "yes" and "no" very well). The rest of the numeric columns are left untouched.

In [3]:

```
# Isolate target data
churn_result = churn_df['Churn?']
y = np.where(churn_result == 'True.',1,0)

# We don't need these columns
to_drop = ['State','Area Code','Phone','Churn?']
churn_feat_space = churn_df.drop(to_drop,axis=1)

# 'yes'/'no' has to be converted to boolean values
# NumPy converts these from boolean to 1. and 0. later
yes_no_cols = ["Int'l Plan","VMail Plan"]
churn_feat_space[yes_no_cols] = churn_feat_space[yes_no_cols] == 'yes'

# Pull out features for future use
features = churn_feat_space.columns

X = churn_feat_space.as_matrix().astype(np.float)

# This is important
from sklearn.preprocessing import StandardScaler
scaler = StandardScaler()
X = scaler.fit_transform(X)

print "Feature space holds %d observations and %d features" % X.shape
print "Unique target labels:", np.unique(y)
```

Learn More
Facebook
Twitter
LinkedIn
Reddit

```
Feature space holds 3333 observations and 17 features
Unique target labels: [0 1]
```

One slight side note. Many predictors care about the relative size of different features even though those scales might be arbitrary. For instance: the number of points a basketball team scores per game will naturally be a couple orders of magnitude larger than their win percentage. But this doesn't mean that the latter is 100 times less significant. `StandardScaler` fixes this by normalizing each feature to a range of around 1.0 to -1.0 thereby preventing models from misbehaving. Well, at least for that reason.

Great, I now have a feature space '`X`' and a set of target values '`y`'. On to the predictions!

How good is your model?

Express, test, cycle. A machine learning pipeline should be anything but static. There are always new features to design, new data to use, new classifiers to consider each with unique parameters to tune. And for every change it's critical to be able to ask, *"Is the new version better than the last?"* So how do I do that?

Learn More
Facebook
Twitter
Linkedin
Reddit

As a good start, cross validation will be used throughout this blog. Cross validation attempts to avoid overfitting (training on and predicting the same datapoint) while still producing a prediction for each observation dataset. This is accomplished by systematically hiding different subsets of the data while training a set of models. After training, each model predicts on the subset that had been hidden to it, emulating multiple train-test splits. When done correctly, every observation will have a 'fair' corresponding prediction.

Here's what that looks like using `scikit-learn` libraries.

In [4]:

```
from sklearn.cross_validation import KFold


def run_cv(X,y,clf_class,**kwargs):
    # Construct a kfolds object
    kf = KFold(len(y),n_folds=5,shuffle=True)
    y_pred = y.copy()

    # Iterate through folds
    for train_index, test_index in kf:
        X_train, X_test = X[train_index], X[test_index]
        y_train = y[train_index]
        # Initialize a classifier with key word arguments
        clf = clf_class(**kwargs)
        clf.fit(X_train,y_train)
        y_pred[test_index] = clf.predict(X_test)
    return y_pred
```

I've decided to compare three fairly unique algorithms support vector machines, random forest, and k-nearest-neighbors. Nothing fancy here, just passing each to cross validation and determining how often the classifier predicted the correct class.

Learn More
Facebook
Twitter
Linkedin
Reddit

In [5]:

```
from sklearn.svm import SVC
from sklearn.ensemble import RandomForestClassifier as RF
from sklearn.neighbors import KNeighborsClassifier as KNN

def accuracy(y_true,y_pred):
    # NumPy interprets True and False as 1. and 0.
    return np.mean(y_true == y_pred)

print "Support vector machines:"
print "%.3f" % accuracy(y, run_cv(X,y,SVC))
print "Random forest:"
print "%.3f" % accuracy(y, run_cv(X,y,RF))
print "K-nearest-neighbors:"
print "%.3f" % accuracy(y, run_cv(X,y,KNN))
```

```
Support vector machines:
0.918
Random forest:
0.943
K-nearest-neighbors:
0.896
```

Random forest won, right?

Precision and recall

Learn More
Facebook
Twitter
LinkedIn
Reddit

Measurements aren't golden formulas which always spit out high numbers for good models and low numbers for bad ones. Inherently they convey something sentiment about a model's performance, and it's the job of the human designer to determine each number's validity. The problem with accuracy is that outcomes aren't necessarily equal. If my classifier predicted a customer would churn and they didn't, that's not the best but it's forgivable. However, if my classifier predicted a customer would return, I didn't act, and then they churned... that's really bad.

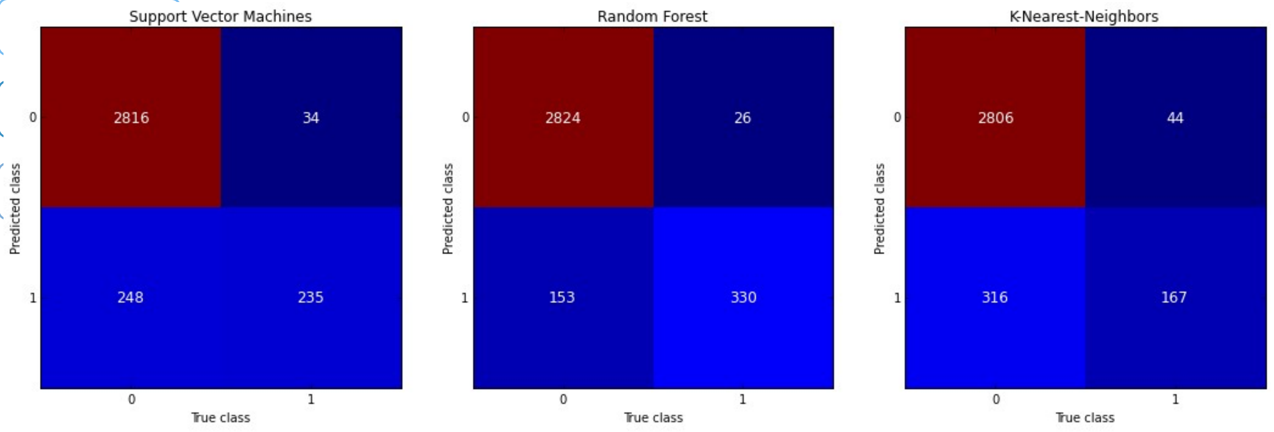
I'll be using another built in `scikit-learn` function to construction a confusion matrix. A confusion matrix is a way of visualizing predictions made by a classifier and is just a table showing the distribution of predictions for a specific class. The x-axis indicates the true class of each observation (if a customer churned or not) while the y-axis corresponds to the class predicted by the model (if my classifier said a customer would churned or not).

In [6]:

```
from sklearn.metrics import confusion_matrix

y = np.array(y)
class_names = np.unique(y)

confusion_matrices = [
    ( "Support Vector Machines", confusion_matrix(y,run_cv(X,y,SVC)) ),
    ( "Random Forest", confusion_matrix(y,run_cv(X,y,RF)) ),
    ( "K-Nearest-Neighbors", confusion_matrix(y,run_cv(X,y,KNN)) ),
]

# Pyplot code not included to reduce clutter
from churn_display import draw_confusion_matrices
%matplotlib inline

draw_confusion_matrices(confusion_matrices,class_names)
```

Learn More

Facebook



An important question to ask might be, *When an individual churns, how often does my classifier predict that correctly?* This measurement is called "recall" and a quick look at these diagrams can demonstrate that random forest is clearly best for this criteria. Out of all the churn cases (outcome " 1 ") random forest correctly retrieved 330 out of 482. This translates to a churn "recall" of about 68% ($330/482 \approx 2/3$), far better than support vector machines ($\approx 50\%$) or k-nearest-neighbors ($\approx 35\%$).

Another question of importance is "precision" or, *When a classifier predicts an individual will churn, how often does that individual actually churn?* The differences in semantic are small from the previous question, but it makes quite a different. Random forest again out preforms the other two at about 93% precision (330 out of 356) with support vector machines a little behind at about 87% (235 out of 269). K-nearest-neighbors lags at about 80% .

While, just like accuracy, precision and recall still rank random forest above SVC and KNN, this won't always be true. When different measurements do return a different pecking order, understanding the values and trade-offs of each rating should effect how you proceed.

Thinking in Probabilities

Decision making often favors probability over simple classifications. There's plainly more information in statements like *"there's a 20% chance of rain tomorrow"* and *"about 55% of test takers pass the California bar exam"* than just saying *"it shouldn't rain tomorrow"* or *"you'll probably pass."* Probability predictions for churn also allow us to gauge a customers expected value, and their expected loss. Who do you want to reach out to first, the client with a 80% churn risk who pays $20,000 annually, or the client who's worth $100,000 a year with a 40% risk? How much should you spend on each client?

While I'm moving a bit away from my expertise, being able to ask that question requires producing predictions a little differently. However, `scikit-learn` makes moving to probabilities easy; my three models have `predict_proba()` built right into their class objects. This is the same cross validation code with only a few lines changed.

In [7]:

Learn More
Facebook
Twitter
Linkedin
Reddit

```python
def run_prob_cv(X, y, clf_class, **kwargs):
    kf = KFold(len(y), n_folds=5, shuffle=True)
    y_prob = np.zeros((len(y),2))
    for train_index, test_index in kf:
        X_train, X_test = X[train_index], X[test_index]
        y_train = y[train_index]
        clf = clf_class(**kwargs)
        clf.fit(X_train,y_train)
        # Predict probabilities, not classes
        y_prob[test_index] = clf.predict_proba(X_test)
    return y_prob
```

How good is good?

Learn More
Facebook
Twitter
Linkedin
Reddit

Determining how good a predictor which gives *probabilities* rather than *classes* is a bit more difficult. If I predict there's a 20% likelihood of rain tomorrow I don't get to live out all the possible outcomes of the universe. It either rains or it doesn't.

What helps is that the predictors aren't making one prediction, they're making 3000+. So for every time I predict an event to occur 20% of the time I can see how often those events actually happen. Here's I use `pandas` to help me compare the predictions made by random forest against the actual outcomes.

In [8]:

```python
import warnings
warnings.filterwarnings('ignore')

# Use 10 estimators so predictions are all multiples of 0.1
pred_prob = run_prob_cv(X, y, RF, n_estimators=10)
pred_churn = pred_prob[:,1]
```

```
is_churn = y == 1

# Number of times a predicted probability is assigned to an observation
counts = pd.value_counts(pred_churn)

# calculate true probabilities
true_prob = {}
for prob in counts.index:
    true_prob[prob] = np.mean(is_churn[pred_churn == prob])
    true_prob = pd.Series(true_prob)

# pandas-fu
counts = pd.concat([counts,true_prob], axis=1).reset_index()
counts.columns = ['pred_prob', 'count', 'true_prob']
counts
```

Learn More
Facebook
Twitter
Linkedin
Reddit

Out[8]:

	pred_prob	count	true_prob
0	0.0	1765	0.028329
1	0.1	693	0.025974
2	0.2	269	0.070632
3	0.3	123	0.138211
4	0.4	77	0.350649
5	0.5	54	0.518519
6	0.6	73	0.835616
7	0.7	76	0.855263
8	0.8	70	0.957143
9	0.9	75	0.973333
10	1.0	58	1.000000

11 rows × 3 columns

We can see that random forests predicted that 75 individuals would have a 0.9 probability of churn and in actuality that group had a ~0.97 rate.

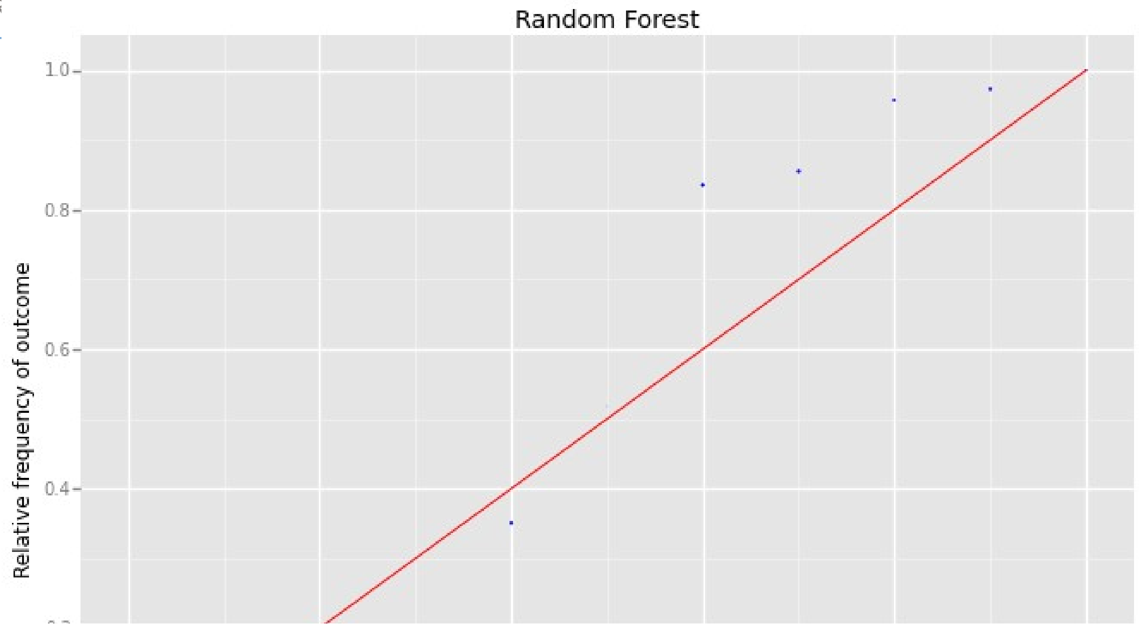
Calibration and Discrimination

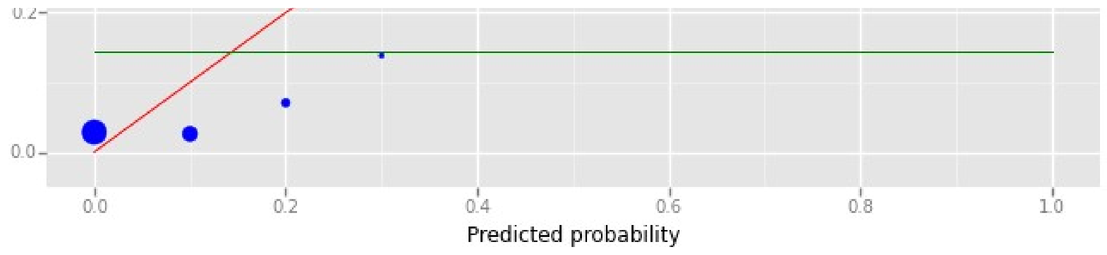
Using the `DataFrame` above I can draw a pretty simple graph to help visualize probability measurements. The x axis represents the churn probabilities which random forest assigned to a group of individuals. The y axis is the actual rate of churn within that group, and each point is scaled relative to the size of the group.

In [9]:

```
from ggplot import *
%matplotlib inline


baseline = np.mean(is_churn)
ggplot(counts,aes(x='pred_prob',y='true_prob',size='count')) + \
    geom_point(color='blue') + \
    stat_function(fun = lambda x: x, color='red') + \
    stat_function(fun = lambda x: baseline, color='green') + \
    xlim(-0.05,  1.05) + ylim(-0.05,1.05) + \
    ggtitle("Random Forest") + \
    xlab("Predicted probability") + ylab("Relative frequency of outcom
e")
```

Learn More
Facebook
Twitter
Linkedin
F





You may have also noticed the two lines I drew with `stat_function()`.

The red line represents a perfect prediction for a given group, or when the churn probability forecasted equals the outcome frequency. The green line shows the baseline probability of churn. For this dataset it's about 0.15.

Calibration is a relatively simple measurement and can be summed up as so: *Events predicted to happen 60% of the time should happen 60% of the time.* For all individuals I predict to have a churn risk of between 30 and 40%, the true churn rate for that group should be about 35%. For the graph above think of it as, *How close are my predictions to the red line?*

Learn More
Facebook
Twitter
LinkedIn
Reddit

Discrimination measures *How far are my predictions away from the green line?* Why is that important?

Well, if I assign a churn probability of 15% to every individual I'll have near perfect calibration due to averages, but I'll be lacking any real insight. Discrimination gives a model a better score if it's able to isolate groups which are further from the base set.

`Scikit-learn` doesn't come with these measurements, meaning I've had to implement them myself. For everyone's sake I've kept the math and source code out of this blog. Equations are replicated from Yang, Yates, and Smith (1991) and the code I wrote in the `churn_measurements` import below can be found on GitHub here.

In [10]:

```
from churn_measurements import calibration, discrimination
```

Let's see how my three models fair on these measurements.

In [11]:

```
def print_measurements(pred_prob):
    churn_prob, is_churn = pred_prob[:,1], y == 1
    print "  %-20s %.4f" % ("Calibration Error", calibration(churn_prob, 
is_churn))
    print "  %-20s %.4f" % ("Discrimination", discrimination(churn_prob, 
is_churn))

    print "Note -- Lower calibration is better, higher discrimination is 
better"

    print "Support vector machines:"
    print_measurements(run_prob_cv(X,y,SVC,probability=True))

    print "Random forests:"
    print_measurements(run_prob_cv(X,y,RF,n_estimators=18))

    print "K-nearest-neighbors:"

print_measurements(run_prob_cv(X,y,KNN))
```

Learn More
Facebook
Twitter
Linkedin
Reddit

```
Note -- Lower calibration is better, higher discrimination is bett
er
Support vector machines:
Calibration Error    0.0017
Discrimination       0.0667
Random forests:
Calibration Error    0.0079
Discrimination       0.0830
K-nearest-neighbors:
```

```
Calibration Error    0.0022
Discrimination       0.0449
```

Unlike the classification comparisons earlier, random forest isn't as clearly the front-runner here. While it's good at differentiating between high and low probability churn events, it has trouble assigning an accurate probability estimate to those events. For example the group which random forest predicts to have a 30% churn rate actually had a true churn rate of 14%. Clearly there's more work to be done, but I leave that to you as a challenge.

Putting the model to use with Yhat

Time to upload a model to the cloud! In order to show some cool functionality, I'm going to go ahead and create a test set from the original churn data using `test_train_split()` from sklearn. From there, I fit a support vector classifier for my deployment.

Learn More
Facebook
Twitter
Linkedin
Reddit

In [12]:

```
from sklearn.cross_validation import train_test_split

train_index,test_index = train_test_split(churn_df.index)
clf = SVC(probability=True)
clf.fit(X[train_index],y[train_index])

test_churn_df = churn_df.ix[test_index]
test_churn_df.to_csv("test_churn.csv")
```

The model I'm going to deploy using `yhat` replicates the pipeline of this blog with a few modifications. Because I already defined variables within my global scope such as `yes_no_cols`, `features`, and `scaler` I can just use them without having to specify them further.

On the methodological side I've added a few calculations. First the customer worth has been added (the sum of the total charges to that individual). Combining this value with probability of churn creates a very important measurement: the expected loss of revenue from that customer. This is where an accurate prediction model plays an important role as it's impossible to produce these values with only classifications.

In [13]:

```
from yhat import Yhat,YhatModel,preprocess

class ChurnModel(YhatModel):
    # Type casts incoming data as a dataframe
    @preprocess(in_type=pd.DataFrame,out_type=pd.DataFrame)
    def execute(self,data):
        # Collect customer meta data
        response = data[['Area Code','Phone']]
        charges = ['Day Charge','Eve Charge','Night Charge','Intl Charge']
        response['customer_worth'] = data[charges].sum(axis=1)
        # Convert yes no columns to bool
        data[yes_no_cols] = data[yes_no_cols] == 'yes'
        # Create feature space
        X = data[features].as_matrix().astype(float)
        X = scaler.transform(X)
        # Make prediction
        churn_prob = clf.predict_proba(X)
        response['churn_prob'] = churn_prob[:,1]
        # Calculate expected loss by churn
        response['expected_loss'] = response['churn_prob'] * response['customer_worth']
        response = response.sort('expected_loss', ascending=False)
        # Return response DataFrame
```

Learn More
Facebook
Twitter
Linkedin
Reddit

```
        return response

yh = Yhat(
    "e[at]yhathq.com",
    "MY API KEY",
    "http://cloud.yhathq.com/"
)

response = yh.deploy("PythonChurnModel",ChurnModel,globals())
```

```
        Are you sure you want to deploy? (y/N): y
```

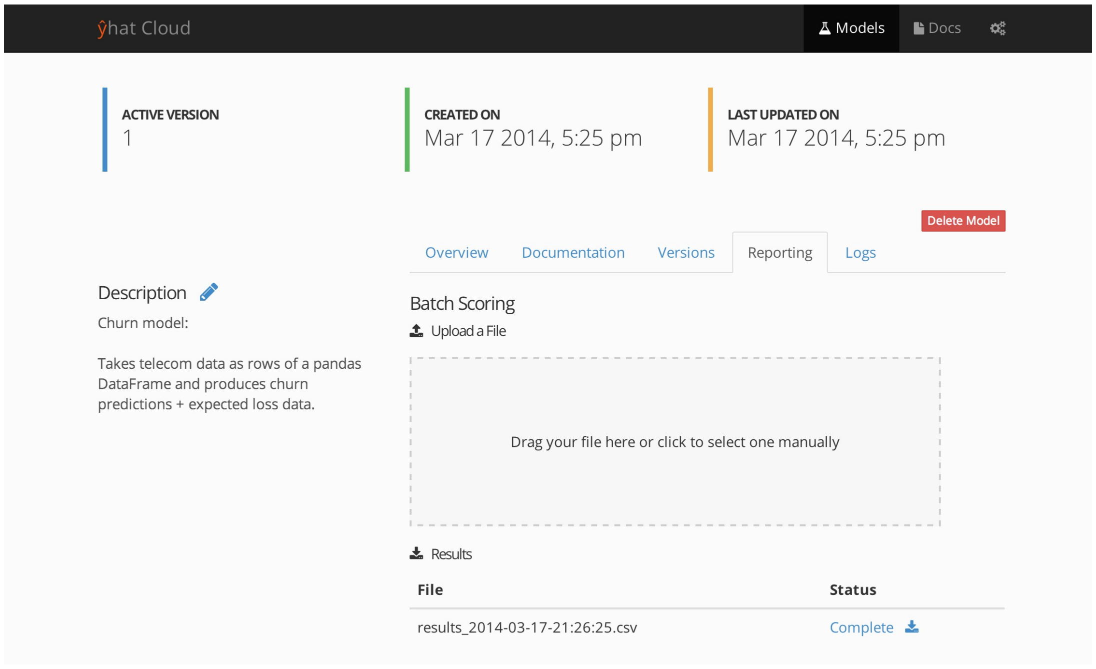
Yhat batch mode

Learn More
Facebook
Twitter
Linkedin
Reddit

There comes a point when data science tools need to stop being scripts on an EC2 instance and start solving problems. In this case, empowering a retention team by warning them about customers likely to churn.

Our *M.O.* here at Yhat is finding ways to make data science applicable and practical as quickly as possible. Because my `execute()` function takes and returns a `DataFrame`, Yhat allows me to invoke my routine through a batch-scoring mode. The concept is simple. Upload a csv file from anywhere, the model pipeline is executed and the user gets a csv file back. This means that my method for scoring customers for churn-risk can be utilized by anyone else at my company regardless of their technical know-how, understanding of machine learning, or technical dependencies like `Python` or `R`.

Logging into cloud.yhathq.com and selecting my model gives me the following screen. The csv file I uploaded was the training data I created in the last section--in practice, this would be a new file exported from our CRM or customer database in the same format as the one I used to train the model.


ŷhat Cloud | Models | Docs

ACTIVE VERSION
1

CREATED ON
Mar 17 2014, 5:25 pm

LAST UPDATED ON
Mar 17 2014, 5:25 pm

Delete Model

Overview | Documentation | Versions | Reporting | Logs

Description

Churn model:

Takes telecom data as rows of a pandas DataFrame and produces churn predictions + expected loss data.

Batch Scoring

Upload a File

Drag your file here or click to select one manually

Results

File	Status
results_2014-03-17-21:26:25.csv	Complete

Wait a second, download the resulting file at the bottom of the page when it's ready, and open it in Excel.

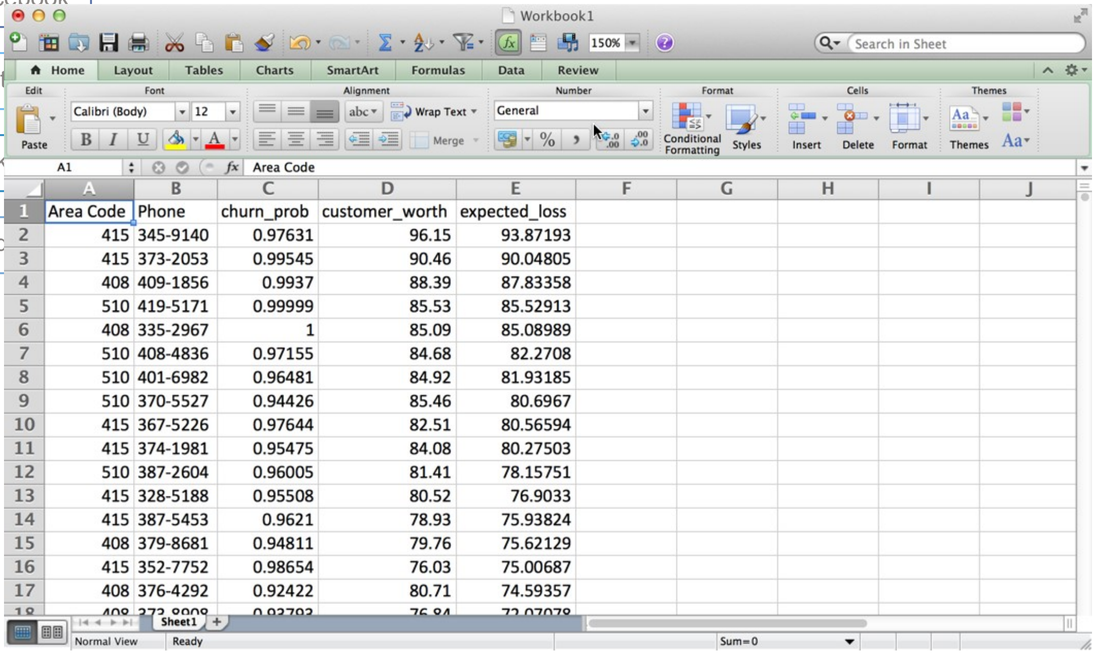
Learn More

Facebook

Twi

Link

Rec

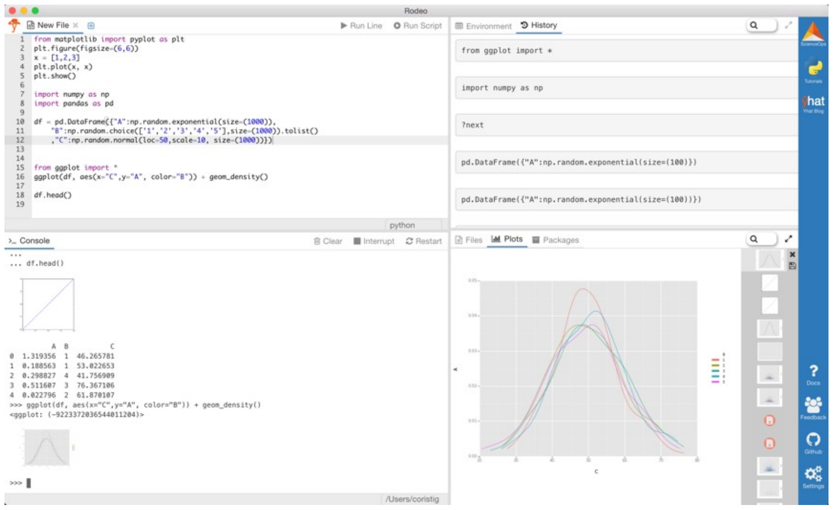


Area Code	Phone	churn_prob	customer_worth	expected_loss
415	345-9140	0.97631	96.15	93.87193
415	373-2053	0.99545	90.46	90.04805
408	409-1856	0.9937	88.39	87.83358
510	419-5171	0.99999	85.53	85.52913
408	335-2967	1	85.09	85.08989
510	408-4836	0.97155	84.68	82.2708
510	401-6982	0.96481	84.92	81.93185
510	370-5527	0.94426	85.46	80.6967
415	367-5226	0.97644	82.51	80.56594
415	374-1981	0.95475	84.08	80.27503
510	387-2604	0.96005	81.41	78.15751
415	328-5188	0.95508	80.52	76.9033
415	387-5453	0.9621	78.93	75.93824
408	379-8681	0.94811	79.76	75.62129
415	352-7752	0.98654	76.03	75.00687
408	376-4292	0.92422	80.71	74.59357

And there you go. Over 800 customers ranked and analyzed via drag and drop.

Learn More Facebook Twitter Linkedin Reddit

Our Products



```python
from matplotlib import pyplot as plt
plt.figure(figsize=(6,6))
x = [1,2,3]
plt.plot(x, x)
plt.show()

import numpy as np
import pandas as pd

df = pd.DataFrame({"A":np.random.exponential(size=(1000)),
    "B":np.random.choice(['1','2','3','4','5'],size=(1000)).tolist()
    ,"C":np.random.normal(loc=50,scale=10, size=(1000))})


from ggplot import *
ggplot(df, aes(x="C",y="A", color="B")) + geom_density()

df.head()
```

```
...
... df.head()

          A  B          C
0  1.319356  1  46.265781
1  0.188563  1  53.022653
2  0.298827  4  41.756909
3  0.511607  3  76.367106
4  0.022796  2  61.870107
>>> ggplot(df, aes(x="C",y="A", color="B")) + geom_density()
<ggplot: (-9223372036544011204)>

>>> 
```

```
from ggplot import *

import numpy as np

?next

pd.DataFrame({"A":np.random.exponential(size=(100)})

pd.DataFrame({"A":np.random.exponential(size=(100))})
```

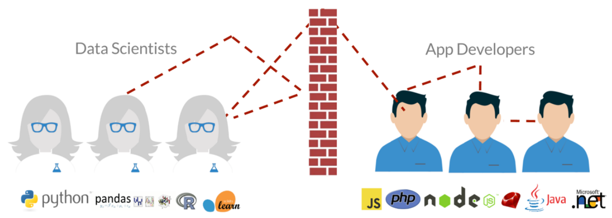
Learn More Facebook Twitter Linkedin Reddit

Rodeo: a native Python editor built for doing data science on your desktop.

DOWNLOAD IT NOW!

---

scienceOPS



ScienceOps: deploy predictive models in production applications without IT.

LEARN MORE

Yhat (pronounced Y-hat) provides data science solutions that let data scientists deploy and integrate predictive models into applications without IT or custom coding.

Contact Us

info@yhathq.com
+1 718 855 2107
+49 15735983455

Learn More

Our Products

Facebook

ScienceOps
Rodeo

Twitter

Learn More

LinkedIn

Company
Blog

Reddit

Jobs
RSS

Newsletter

Email Address

Get Updates

Connect With Us

Made in New York City • © 2016 ŷhat