Using Al Tools to Identify Investment Candidates

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Approach – Build the Models

Create training set of labeled drugs

Drug	Label	
Vioxx	Good Drug	
Mulresso	Good Drug	
Zituxan	Bad Drug	
DPN-15074	Bad Drug	

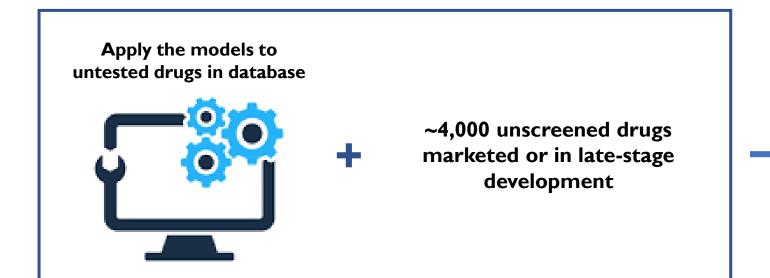
Combined with key drug info from a drug database

Drug	Therapeutic Area	Indications	Designations	Sales 2018	Launch date	Summary
Zeyfalsda	Cancer; Infection	Acute myelogenous leukemia; Adenocarcinoma; Adenoid tumor;	Accelerated Approval; Breakthrough Therapy; Orphan Drug;	1022	Sept 2013	Merck & Co has developed and launched Zeyfalda with

Build predictive models using Al tools

Drug	Label	Predicted Probability	Predicted Label
Vioxx	Good	97%	Good
Mulresso	Good	70%	Good
Zituxan	Bad	58%	Good 🗙
DPN- 15074	Bad	30%	Bad

Approach – Screen Untested Drugs



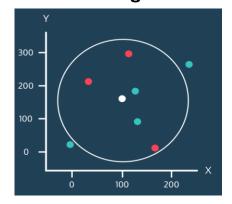
Identify most likely drug list candidates

Drug	Predicted probability		
Varadolone	95%		
RTX-5700	93%		
Denilopan	93%		
GTX-1650	88%		

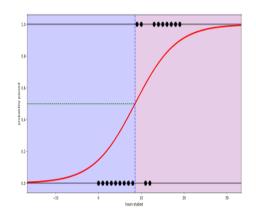
Building the Models – The Four Models

Algorithm	Description	Data types	Notes
K-nearest neighbors (KNN)	 Calculates the similarity (distance) between each point Labels points according to the given for closest neighbors 	NumericBinary	 Little theoretical basis, but works well in practice Computationally expensive
Logistical regression (LR)	Linear regression mapped to a sigmoidal function so that results are between 0 and 1	NumericBinary	 Well established technique Can estimate impact of individual variables
Support vector machines (SVM)	achines groups of data		Conceptually simpleComputationally cheap
Naïve Bayes (Bayes)	Labels based on word frequency and prior frequency of two labels	• Text	Simple algorithm for text analysisFamously used in spam filters

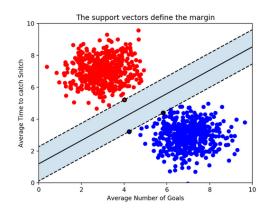
K-nearest neighbors



Logistical regression



Support Vector Machines



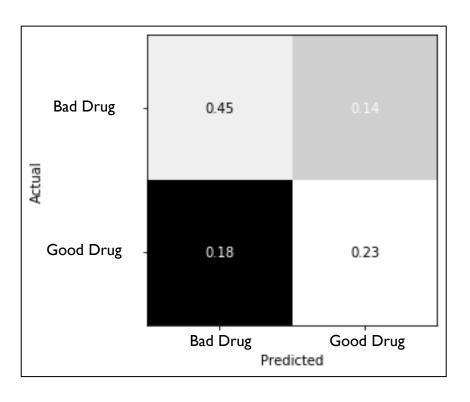
Naïve Bayes

$$P(A \mid B) = \frac{P(B \mid A) \cdot P(A)}{P(B)}$$

	Percent Spam	Percent Not Span
Urgent:	0.96	0.04
Urgent: limited	0.97	0.03
Urgent: limited time	0.81	0.19
Urgent: limited time offer	0.93	0.07

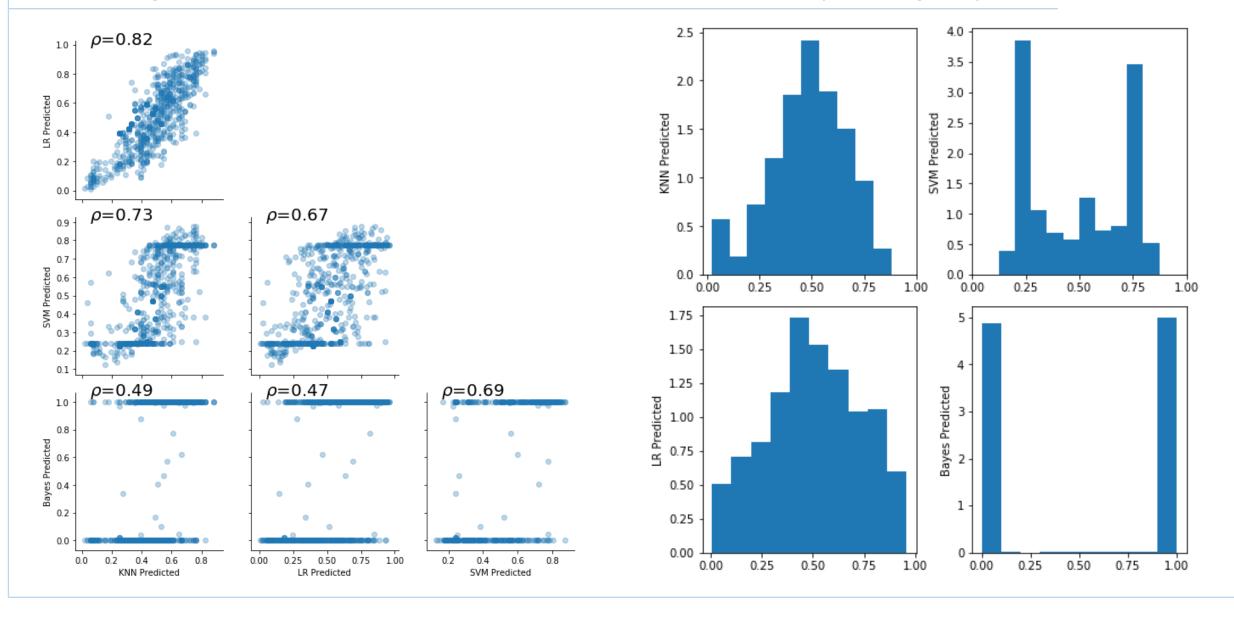
Building the Models - Sample code

```
import pandas as pd
from sklearn.neighbors import KNeighborsClassifier
from sklearn.model selection import train test split
from sklearn import metrics
import matplotlib.pyplot as plt
import prep and analysis functions as paf # custom analysis functions see file
from sklearn.model selection import KFold
# load training set
training_set = pd.read_csv('training_set_standardized.csv')
Part 1 - A - Prepare model for unapproved drugs
#collect columns to input into model
feature columns unapproved = ['Fast Track', 'SPA', 'Orphan', 'Breakthrough', 'RMAT', 'QIDP', 'large public',
                    small public', 'phase III date 2015-2020', 'phase III date 2010-2014', 'phase III date 20''
                   'Infectious disease', 'Psychiatry', 'Oncology', 'Autoimmune/immunology', 'Dermatology',
                   'Neurology', 'Respiratory', 'Endocrine', 'Hematology', 'Cardiovascular', 'Not Specified',
                   'Gastroenterology (non inflammatory bowel disease)', 'Obstetrics/Gynecology', 'Metabolic',
                   'Allergy', 'Ophthalmology', 'Urology', 'ENT/Dental', 'Renal<sup>†</sup>, 'Orthopedics',
                   'Rheumatology (non autoimmune)', 'likelihood %', 'diff from avg']
# create features and labels list
features unapproved = training set.loc[training set['approved']==0, feature columns unapproved]
labels unapproved = training set.loc[training set['approved']==0, 'Drug List Status']
# build training/testing set
x train, x test, y train, y test = train test split(features unapproved, labels unapproved, test size=0.2)
# create classifier object
knn classifier = KNeighborsClassifier(n neighbors=21) # see below for finding optimal value
# train model
knn_classifier.fit(x_train, y_train)
y_pred = knn_classifier.predict(x_test) # create predictions for test set
# quick accuracy check
paf.print_accuracy(y_test, y_pred)
paf.plot confusion matrix(y test, y pred)
paf.plot confusion_matrix_normalized(y_test, y_pred)
```



accuracy = 0.6785714285714286 recall = 0.5652173913043478 precision = 0.6190476190476191 f1 score = 0.5909090909090909

Building the Models - Model Correlation and Distribution (Training Set)



Applying the Models – Model Correlation and Distribution (testing set)

