1 Introducing Test-driven Machine Learning

Our first test

```
Е
_____
ERROR: number_guesser_tests.given_no_information_when_asked_to_guess_t
est
Traceback (most recent call last):
 File "/Users/justin/Envs/default/lib/python2.7/site-packages/nose/ca
se.py", line 197, in runTest
   self.test(*self.arg)
 File "/Users/justin/Documents/Code/Machine-Learning-Test-by-Test/Cha
pter 1/number_guesser_tests.py", line 2, in given_no_information_when_
asked_to_guess_test
   number_guesser = NumberGuesser()
NameError: global name 'NumberGuesser' is not defined
Ran 1 test in 0.002s
FAILED (errors=1)
                    _____
Ran 1 test in 0.002s
0K
```







Perceptively Testing a Perceptron

-20 -40 -60 ∟ -2

Getting started

	Training rate		0.25					
Iteration	Training 1	Training 2	Training label	Weights 1	Weights 2	Weight 1 update	Weight 2 update	Predicted value
1	1	. 1	1	0.96897982	0.97171753	0.968979818	0.971717531	1
1	1	. 0	1	0.96897982	0.97171753	0.968979818	0.971717531	1
1	0	1	1	0.96897982	0.97171753	0.968979818	0.971717531	1
1	C	0	0	0.96897982	0.97171753	0.968979818	0.971717531	0

$$w_{i+1,j} = w_{i,j} + \eta * w_{i,j} * (t_j - p_j)$$

	Α	В	C	D	E	F	G	Н		
1		Training rate		0.25						
2										
3	Iteration	Training 1	Training 2	Training label	Weights 1	Weights 2	Weight 1 update	Weight 2 update	Predicted val	ue
4	1	1	1	1	0.96897982	0.97171753	=E4+\$D\$1*(\$D4-	\$I4)*B4	1	

$$p_j = \sum w_i * x_i > 0$$

	A	B	C	D	E	F	G	Н	L	J
1		Training rate		0.25						
2										
3	Iteration	Training 1	Training 2	Training label	Weights 1	Weights 2	Weight 1 update	Weight 2 update	Predicted value	le
4	1	1	1 1	1	0.96897982	0.97171753	0.968979818	0.971717531	=IF((B4*E4+C	4*F4)>0,1,0)
5	1	1	. 0	1	0.96897982	0.97171753	0.968979818	0.971717531	1	
6	1	0	1	1	0.96897982	0.97171753	0.968979818	0.971717531	1	
7	1	0	0	0	0.96897982	0.97171753	0.968979818	0.971717531	0	
0										

	A	B	C	D	E	F	G	Н	
1		Training rate		0.1					
2									
3	Iteration	Training 1	Training 2	Training label	Weights 1	Weights 2	Weight 1 update	Weight 2 update	Predicted value
4	1	5	-1	1	0.431	0.02	0.431	0.02	1
5	1	2	-1	0	0.431	0.02	0.231	0.12	1
6	1	0	-1	0	0.231	0.12	0.231	0.12	0
7	1	-2	-1	0	0.231	0.12	0.231	0.12	0
8	2	5	-1	1	0.231	0.12	0.231	0.12	1
9	2	2	-1	0	0.231	0.12	0.031	0.22	1
10	2	0	-1	0	0.031	0.22	0.031	0.22	0
11	2	-2	-1	0	0.031	0.22	0.031	0.22	0
12	3	5	-1	1	0.031	0.22	0.531	0.12	0
13	3	2	-1	0	0.531	0.12	0.331	0.22	1
14	3	0	-1	0	0.331	0.22	0.331	0.22	0
15	3	-2	-1	0	0.331	0.22	0.331	0.22	0
16	4	5	-1	1	0.331	0.22	0.331	0.22	1
17	4	2	-1	0	0.331	0.22	0.131	0.32	1
18	4	0	-1	0	0.131	0.32	0.131	0.32	0
19	4	-2	-1	0	0.131	0.32	0.131	0.32	0
20	5	5	-1	1	0.131	0.32	0.131	0.32	1
21	5	2	-1	0	0.131	0.32	0.131	0.32	0
22	5	0	-1	0	0.131	0.32	0.131	0.32	0
23	5	-2	-1	0	0.131	0.32	0.131	0.32	0

```
FAIL: tests.detect_a_complicated_example_test

Traceback (most recent call last):

    File "/Library/Python/2.7/site-packages/nose-1.3.0-py2.7.egg/nose/ca

se.py", line 197, in runTest

    self.test(*self.arg)

    File "/Users/justin/Documents/Code/test-driven-machine-learning/Chap

ter 2 Redux/tests.py", line 75, in detect_a_complicated_example_test

    "Perceptron should be much better than random. {0} correct".format

(correctly_classified)

AssertionError: Perceptron should be much better than random. 1367 cor

rect
```

```
Ran 5 tests in 0.082s
```

```
FAILED (failures=1)
```



Perceptron accuracy vs training iterations

3

Exploring the Unknown with Multi-armed Bandits

Simulating real world situations



A randomized probability matching algorithm





8



The problem with straight bootstrapping

Multi-armed armed bandit throw down

SimpleBandit: 22443.9230864 RPMBandit: 24567.9045708



4

Predicting Values with

Building the foundations of our model

		OLS Regre	ssion R	esults		
Dep. Variab Model: Method: Date: Time: No. Observa Df Residual Df Model: Covariance	le: tions: s: Type:	dependent_var OLS Least Squares Thu, 19 Feb 2015 20:57:08 30 28 1 nonrobust	R-sq Adj. F-st Prob Log- AIC: BIC:	uared: R-squared: atistic: (F-statistic): Likelihood:		0.005 -0.030 0.1499 0.702 -222.90 449.8 452.6
	coef	std err	t	P> t	[95.0% Co	nf. Int.]
Intercept ind_var_d	224.5840 -1.1946	520.609 3.085	0.431 -0.387	0.669 0.702	-841.836 -7.515	1291.004 5.125
Omnibus: Prob(Omnibu Skew: Kurtosis:	s):	0.043 0.979 -0.017 2.787	Durb Jarq Prob Cond	in-Watson: ue-Bera (JB): (JB): . No.		2.057 0.058 0.971 1.14e+03

0LS	Regression	Resu	lts
-----	------------	------	-----

Dep. Variab	le:	dependent_var	R-squ	uared:		0.182
Model:		OLS	Adj.	R-squared:		0.152
Method:		Least Squares	F-sta	atistic:		6.215
Date:		Thu, 19 Feb 2015	Prob	(F-statistic):		0.0188
Time:		21:16:15	Log-l	ikelihood:		-219.98
No. Observa	tions:	30	AIC:			444.0
Df Residual	s:	28	BIC:			446.8
Df Model:		1				
Covariance	Туре:	nonrobust				
	coet	f std err	t	P> t	[95.0% Conf	. Int.]
Intercept	33.4182	2 70.006	0.477	0.637	-109.982	176.819
ind_var_a	3.0475	1.222	2.493	0.019	0.544	5.551
Omnibus:		0.175	Durb:	in-Watson:		1.811
Prob(Omnibu	s):	0.916	Jarqu	ue-Bera (JB):		0.023
Skew:		-0.053	Prob	(JB):		0.988
Kurtosis:		2.915	Cond	. No.		57.3

OLS Regression Results

Dep. Varia	ble:	dependent_var	R-squared:			0.818
Model:		OLS	Adj. R-squ	ared:		0.804
Method:		Least Squares	F-statisti	c:		60.62
Date:		Thu, 19 Feb 2015	Prob (F-st	atistic):	1.	04e-10
Time:		21:19:56	Log-Likeli	hood:	-	·197.44
No. Observ	ations:	30	AIC:			400.9
Df Residua	ls:	27	BIC:			405.1
Df Model:		2				
Covariance	Type:	nonrobust				
	coef	std err	t P:	> t	[95.0% Conf.	Int.]
Intercept	94.5490	34.216	2.763 0	.010	24.344 1	64.754
ind_var_a	2.7750	0.588	4.720 0	.000	1.569	3.981
ind_var_b	115.1101	11.853	9.712 0	.000	90.791 1	39.430
Omnibus:		0.248	Durbin-Wat	son:		2.031
Prob(Omnib	us):	0.883	Jarque-Ber	a (JB):		0.442
Skew:		-0.101	Prob(JB):			0.802
Kurtosis:		2.441	Cond. No.			58.5

Dep. Varia	ble:	dependent	t_var	R-sq	uared:		0.845
Model:		-	0LS	Adj.	R-squared:		0.820
Method:		Least Sq	uares	F-st	atistic:		34.12
Date:		Thu, 19 Feb	2015	Prob	(F-statisti	c):	8.64e-10
Time:		21:	33:11	Log-	Likelihood:		-195.00
No. Observa	ations:		30	AIC:			400.0
Df Residua	ls:		25	BIC:			407.0
Df Model:			4				
Covariance	Type:	nonre	obust				
	coef	std err		t	P> t	[95.0% C	onf. Int.]
Intercept	286.7307	225.631		1.271	0.216	-177.965	751.427
ind_var_a	2.5552	0.574		4.453	0.000	1.373	3.737
ind_var_b	112.2556	11.438		9.814	0.000	88.698	135.813
ind_var_c	-6.4966	3.134		-2.073	0.049	-12.951	-0.042
ind_var_d	-0.4223	1.293	-	-0.327	0.747	-3.085	2.240
Omnibus:			0.100	Durb	in-Watson:		2.208
Prob(Omnibu	us):	(0.951	Jarg	ue-Bera (JB)	:	0.030
Skew:			0.028	Prob	(JB):		0.985
Kurtosis:		:	2.856	Cond	. No.		1.19e+03

OLS Regression Results

•

Ran 1 test in 0.414s

0K

-

OLS Regression Results

Dep. Variable:	depende	nt_var	R-sq	uared:		0.987	
Model:		0LS	Adj.	R-squared:		0.984	
Method:	Least S	quares	F-st	atistic:		356.7	
Date:	Thu, 19 Fe	b 2015	Prob	(F-statist	ic):	1.07e-21	
Time:	22	:02:03	Log-	Likelihood:		-158.16	
No. Observations:		30	AIC:			328.3	
Df Residuals:		24	BIC:			336.7	
Df Model:		5					
Covariance Type:	non	robust					
	coef	std	err	t	P> t	[95.0% Con1	. Int.]
Intercept	25.6266	24.	999	1.025	0.316	-25.968	77.221
ind_var_a	2.7083	0.	171	15.820	0.000	2.355	3.062
ind_var_b	-1.5527	8.	798	-0.176	0.861	-19.712	16.606
ind_var_c	-0.3917	1.0	036	-0.378	0.709	-2.529	1.746
ind_var_e	-0.2006	0.0	032	-6.231	0.000	-0.267	-0.134
ind_var_b:ind_var_c	5.6450	0.	371	15.225	0.000	4.880	6.410
Omnibus:		0.697	Durb	in-Watson:		2.070	
Prob(Omnibus):		0.706	Jarg	ue-Bera (JB):	0.584	
Skew:		-0.318	Prob	(JB):		0.747	
Kurtosis:		2.750	Cond	. No.		1.48e+03	

5 Making Decisions Black and White with Logistic Regression

Generating logistic data

Logit Regression Results									
Dep. Variable:	У	No. Observations:	1000						
Model:	Logit	Df Residuals:	998						
Method:	MLE	Df Model:	1						
Date:	Sun, 01 Mar 2015	Pseudo R-squ.:	0.1476						
Time:	16:02:11	Log-Likelihood:	-589.61						
converged:	True	LL-Null:	-691.69						
		LLR p-value:	2.598e-46						

	coef	std err	z	P> z	[95.0% Conf. Int.]
Intercept	-1.8773	0.156	-12.055	0.000	-2.182 -1.572
x	0.0349	0.003	12.897	0.000	0.030 0.040

Measuring model accuracy



Generating a more complex example

Test driving our model

```
F
  _____
  FAIL: logistic_regression_tests.logistic_regression_test
  Traceback (most recent call last):
   File "/Library/Python/2.7/site-packages/nose-1.3.0-py2.7.egg/nose/ca
  se.py", line 197, in runTest
    self.test(*self.arg)
   File "/Users/justin/Documents/Code/Machine-Learning-Test-by-Test/Cha
  pter 5/logistic_regression_tests.py", line 13, in logistic_regression_
  test
    assert auc > .6, 'AUC should be significantly above random'
  AssertionError: AUC should be significantly above random
  Optimization terminated successfully.
        Current function value: 0.426086
        Iterations 6
  AUC score: 0.510791645978
   ----- >> end captured stdout << -----
                        ------
  Ran 1 test in 0.527s
  FAILED (failures=1)
                 Logit Regression Results
_____
Dep. Variable:
                  y No. Observations: 1000
                                                998
Model:
                    Logit Df Residuals:
Method:
Date:
Time:
                      MLE
                          Df Model:
                                                   1
             21:16:05 rseudo R-squ.:
21:16:05 Log-Likelihood:
True LL-Null
                          Pseudo R-squ.:
                                            0.0001789
            Sun, 01 Mar 2015
                                               -426.09
converged:
                                              -426.16
                          LLR p-value:
                                               0.6962
_____
       coef std err z P>|z| [95.0% Conf. Int.]
_____
Intercept 1.8273 0.292 6.258 0.000 1.255 2.400
variable_d -0.0167 0.043 -0.390 0.696 -0.101 0.067
_____
```

Logit Re	gression	Resu	lts
----------	----------	------	-----

Dep. Variable:			y No.	Observations:		1000
Model:		Logi	it DfR	esiduals:		997
Method:		ML	.E DfM	odel:		2
Date:	Sun	, 01 Mar 201	L5 Pseu	do R-squ.:	1	0.06133
Time:		21:36:5	58 Log-	Likelihood:		-400.03
converged:		Tru	e LL-N	ull:		-426.16
-			LLR	p-value:	4.	464e-12
	coef	std err	z	P> z	[95.0% Conf	. Int.]
Intercept	-2.7924	0.852	-3.278	0.001	-4.462	-1.123
variable_b	0.0878	0.014	6.445	0.000	0.061	0.114
variable_c	-0.1242	0.045	-2.783	0.005	-0.212	-0.037

AUC score: 0.678741000497

Logit Regression Results

Dep. Variable:					У	No.	Observations	:		1000
Model:				L	.ogit	Df R	esiduals:			996
Method:					MLE	Df M	lodel:			3
Date:	1	Sun,	01	Mar	2015	Pseu	do R-squ.:		6	0.2088
Time:				21:4	4:45	Log-	Likelihood:		-3	337.19
converged:					True	LL-N	lull:		-4	426.16
						LLR	p-value:		2.45	58e-38
						======				
	coef	5	std	err		z	P> z	[95.0%	Conf.	Int.]
Intercept	-0.9958		0.	932	-	1.068	0.286	-2.82	23	0.832
variable_a	-0.0392		0.	004	-	9.828	0.000	-0.04	- 7	-0.031
variable_b	0.0996		0.	015		6.677	0.000	0.07	0	0.129
variable_c	-0.1487		0.	049	-	3.048	0.002	-0.24	- 4	-0.053

AUC score: 0.813842167329

7 Optimizing by Choosing a New Algorithm

Upgrading the classifier

....E _____ ERROR: naive_bayes_tests.given_two_classes_with_two_dimension_inputs_t est Traceback (most recent call last): File "/Library/Python/2.7/site-packages/nose-1.3.0-py2.7.egg/nose/ca se.py", line 197, in runTest self.test(*self.arg) File "/Users/justin/Documents/Code/Machine-Learning-Test-by-Test/Cha pter 7/naive_bayes_tests.py", line 76, in given_two_classes_with_two_d imension_inputs_test assert results['class b'] > results['class a'], "Should classify a s class b because of dimension 2." ValueError: The truth value of an array with more than one element is ambiguous. Use a.any() or a.all() {'class b': array([0.379657 , 0.99954911]), 'class a': array([6.2 0342995e-01, 4.50893925e-04])} _____ Ran 7 tests in 0.157s FAILED (errors=1)

19

```
....F
_____
FAIL: naive_bayes_tests.given_two_classes_with_two_dimension_inputs_te
st
                        _____
Traceback (most recent call last):
 File "/Library/Python/2.7/site-packages/nose-1.3.0-py2.7.egg/nose/ca
se.py", line 197, in runTest
   self.test(*self.arg)
 File "/Users/justin/Documents/Code/Machine-Learning-Test-by-Test/Cha
pter 7/naive_bayes_tests.py", line 76, in given_two_classes_with_two_d
imension_inputs_test
   assert results['class b'] > results['class a'], "Should classify a
s class b because of dimension 2."
AssertionError: Should classify as class b because of dimension 2.
----- >> begin captured stdout << ------
{'class b': 0.5, 'class a': 0.5}
----- >> end captured stdout << -----
  _____
Ran 7 tests in 0.151s
```

FAILED (failures=1)

Applying our classifier

```
----- >> begin captured stdout << ------
   {'mean': 29.13330600000001, 'variance': 28.673036156363999}]}
   Men
   м
   м
   М
   Women
   F
   F
   F
   Ran 10 tests in 1.290s
   FAILED (failures=1)
  assert False
AssertionError:
   ----- >> begin captured stdout << ------
Correct rate: 0.7936, Total: 5000
{'mean': 37.555443373493979, 'variance': 26226.362753873291}]}
----- >> end captured stdout << ------
Ran 11 tests in 20.608s
FAILED (failures=1)
```

Upgrading to Random Forest

8 Exploring Scikit-learn Test First

Getting choosey

```
--------->>> begin captured stdout << ------
Classifier: <choosey.CopyCatClassifier instance at 0x107433f38>; Number right: 0
Classifier: <libs.NaiveBayes.Classifier instance at 0x107433f80>; Number right: 811
Classifier: <libs.RandomForest.Classifier instance at 0x107433fc8>; Number right: 809
<libs.RandomForest.Classifier instance at 0x107433fc8>
```

Developing testable documentation

Decision trees

------Classifier: <choosey.CopyCatClassifier instance at 0x10481b0e0>; Number right: 0 Classifier: <libs.NaiveBayes.Classifier instance at 0x10481b128>; Number right: 827 Classifier: <libs.RandomForest.Classifier instance at 0x10481b170>; Number right: 808 Classifier: <libs.DecisionTree.Classifier instance at 0x10481b1b8>; Number right: 780 <libs.DecisionTree.Classifier instance at 0x10481b1b8>

------ >> end captured stdout << -----

*Chapter 6 & 9 do not have images