Tuning a Weather Model

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Why might weather forecasting be important?

Secret Sauce



INGREDIENTS: COOKED RICE (WATER, LONG GRAIN BROWN RICE, RED RICE), BROCCOLI, SHRIMP (SHRIMP, SALT), WATER, RED BELL PEPPERS, BABY CORN, EDAMAME, SRIRACHA PASTE (CHILI PEPPER PUREE, DISTILLED WHITE VINEGAR, CANE SUGAR, SEA SALT, GARLIC PUREE, EXPELLER PRESSED CANOLA OIL, GARLIC POWDER, XANTHAN GUM), SOY SAUCE (WATER, SOYBEANS, RICE, SALT), DICED ONION, EXPELLER PRESSED CANOLA OIL, GARLIC PUREE (GARLIC, WATER), CORNSTARCH, PAPRIKA OLEORESIN (FOR COLOR), SHRIMP EXTRACT, SALT.

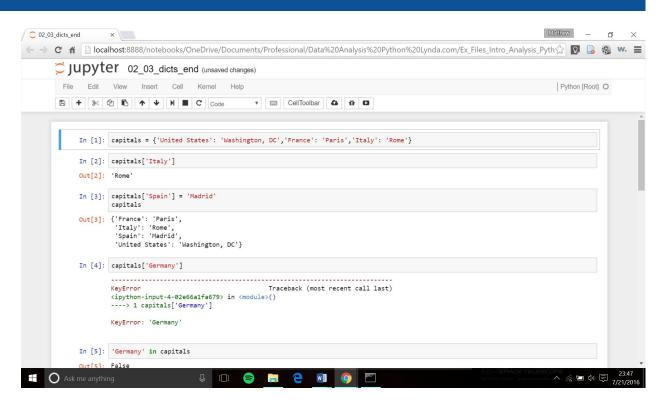
CONTAINS SOY, SHRIMP.

DIST. & SOLD EXCLUSIVELY BY: TRADER JOE'S, MONROVIA, CA 91016

PRODUCT OF CANADA

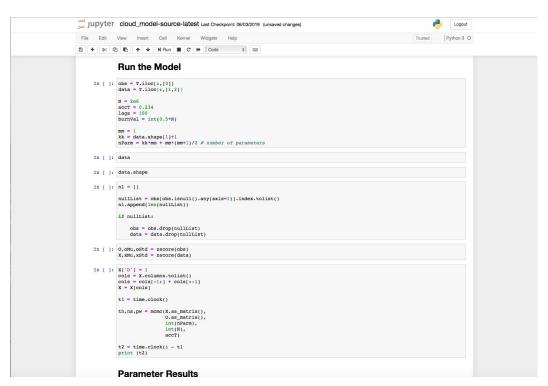
Project Overview

- Jupyter Notebook
- Python



Model Explanation

- Evaluating learning machine
- Using pre-existing data points to determine specific test dates
- The more training data used, the more accurate the test data will be (Hypothesis)



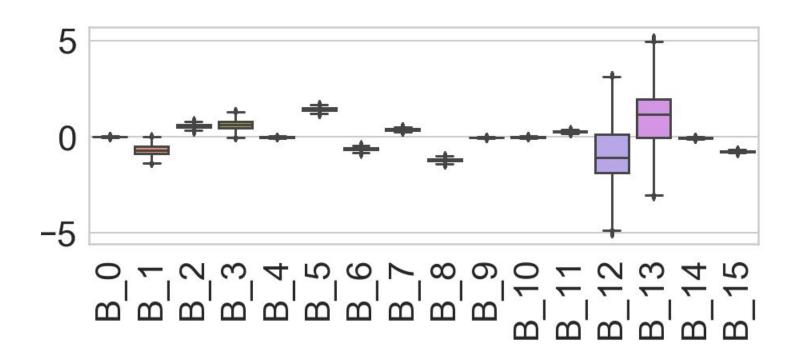
Breaking down the Data Sets

File Name Format: Year/Month/Day/Time - ex. 1606081500Z.pts

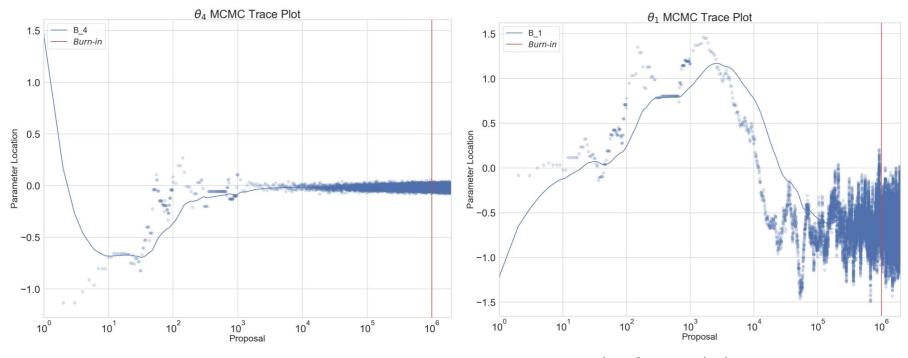
- Cloud data sets have a total of 15 columns
- Wind data sets have a total of 10 columns

Predictors

Box Plot



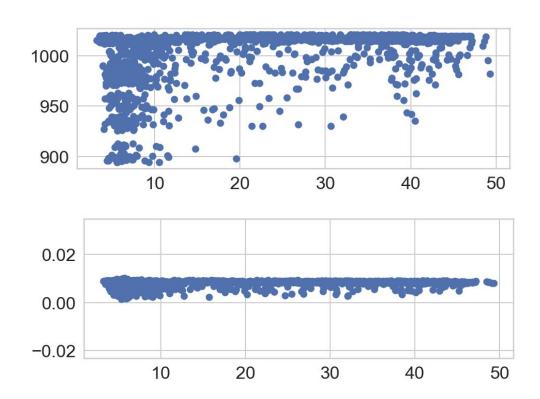
Trace Plot



column 4: maximum vertical motion

column 1: average cloud water

Scatter Plot



column 11: surface pressure

column 8: maximum specific humidity

Most effective/Promising

Cloud - maximum vertical motion, maximum relative humidity, average relative humidity, sea level pressure, surface pressure

Wind - N/A (all columns were needed to run the model)

Understanding the Results

tt: verification

bz: prediction

de: difference between tt and bz

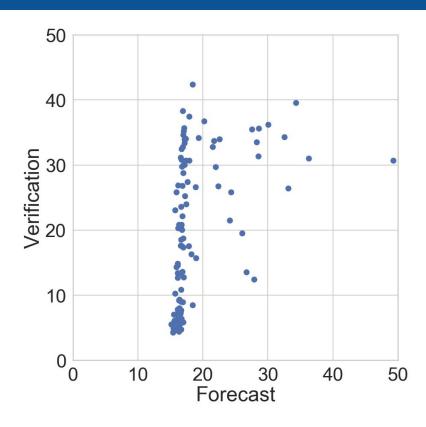
* these arrays were used to generate heat maps, scatterplots, stream plots, and vector plots *

```
de = []
bz = []
tt = []
for idx in range(t.shape[0]):
    pv = array(t.iloc[idx,[1,2,3,4,5]].tolist())
    truth = array(t.iloc[idx,[0]].tolist())
    fs = ppdNorm(bM,cM,pv,
                 xMu.
                 xStd,
                 oMu,
                 oStd.
                 mm, kk)
    fm = np.median(fs,axis=0)
    bz.append(fm)
    tt.append(truth)
    de.append((truth - fm).tolist())
    FS = pd.DataFrame(fs,columns=['I'])
     FS['day'] = idx
     FS = FS.set index(['day'])
    if (idx == 0):
        dfFS = FS.copy()
    else:
        dfFS = pd.concat([dfFS,FS], ignore index=False)
    #del FS
```

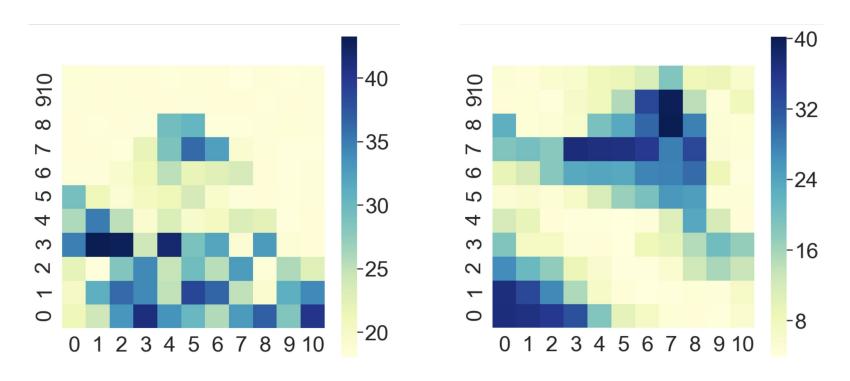
More Parameters More Problems

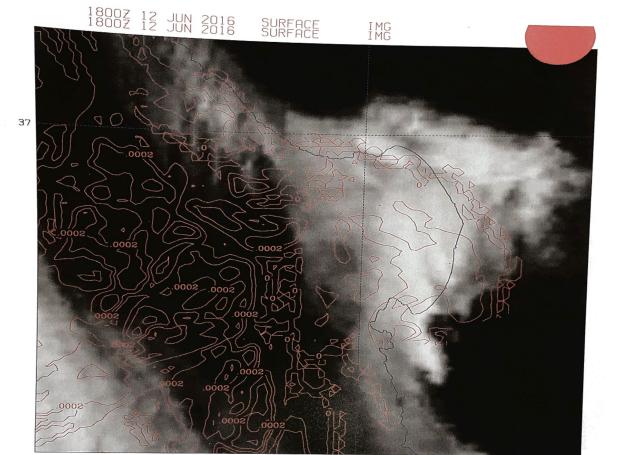
Cloud Model

Scatter Plot: bz vs. tt



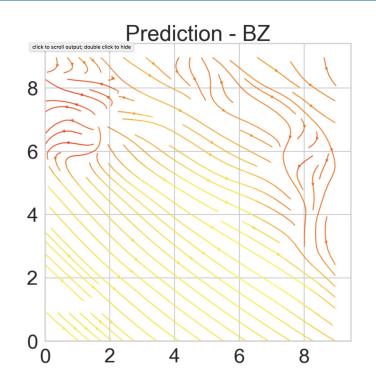
Predicted vs Truth Heat Map

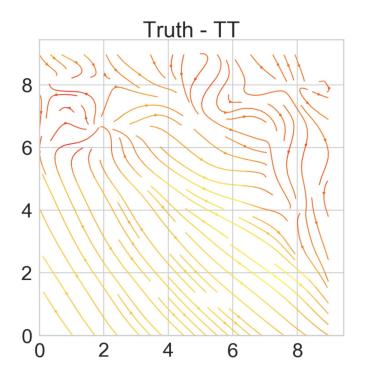




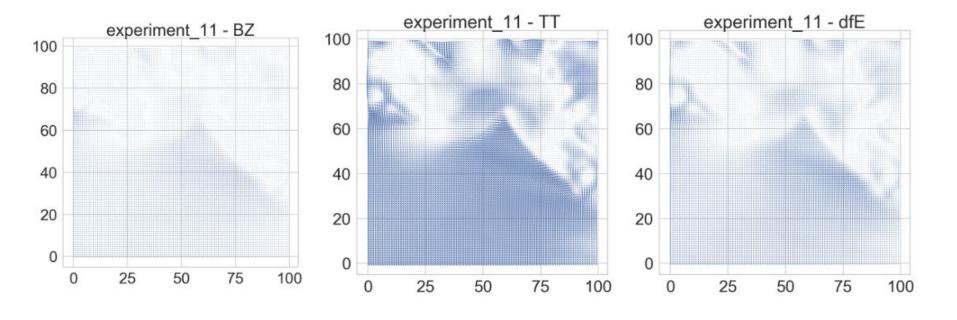
Wind Model

Stream Plot





Vector Plot



-Model Evaluation (and where it breaks)

Integrated Cloud Water and Surface Pressure

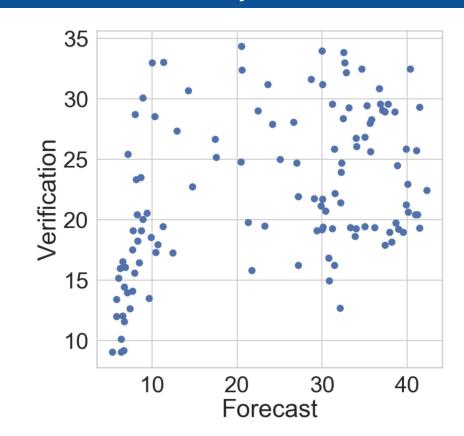
Training data:

160608-11 (4 days)

1500 hrs

Test:

16-06-12-1500



Integrated Cloud Water and Surface Pressure

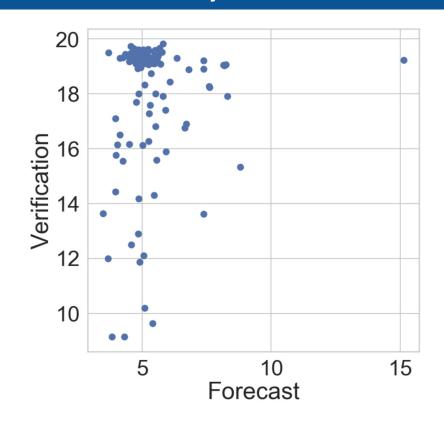
Training data:

160608-11 (4 days)

1500 hrs

Test:

16-06-24-1500



Integrated Cloud Water and Surface Pressure

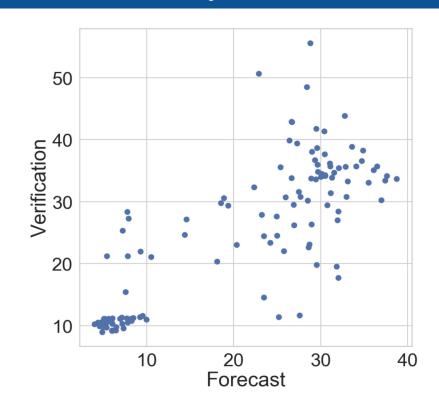
Training data:

160608-160623 (16 days)

1500 hrs

Test:

16-06-24-1500



8 June 2016 1500hrs

	OLS I	Regression	Results				
Dep. Variable: Observe	: Observed cloud reflectivity			R-squared:		0.704	
Model:	0			Adj. R-squared:		0.704	
Method:	Least So		F-statistic:		2375.		
Date:	Tue, 18 3		Prob (F-statistic):		0.00		
Time:		11:44:10	Log-Likelihood:		-32989.		
No. Observations:	10		AIC:		6.600e+04		
Df Residuals:	99		BIC:		6.608e+04		
Df Model:		10					
Covariance Type:	1	nonrobust					
	coef	std err	t	P> t	[0.025	0.975]	
const	-7628.1427	342.949	-22.243	0.000	-8300.393	-6955.893	
Average cloud water	7294.7560	3.08e+04	0.237	0.813	-5.31e+04	6.77e+04	
Maximum cloud water	-1041.7062	1809.909	-0.576	0.565	-4589.492	2506.080	
Integrated cloud water	-1091.6274	2764.131	-0.395	0.693	-6509.881	4326.627	
Maximum Vertical Motion	-0.0161	0.778	-0.021	0.984	-1.541	1.509	
Maximum Relative Humidity	-0.1906	0.020	-9.559	0.000	-0.230	-0.151	
Average Relative Humidity	0.2363	0.016	15.200	0.000	0.206	0.267	
Average Specific Humidity	-5730.5433	211.593	-27.083	0.000	-6145.309	-5315.778	
Max Specific Humidity	6051.7509	305.580	19.804	0.000	5452.753	6650.749	
Sea Level Pressure	7.4645	0.341	21.884	0.000	6.796	8.133	
Surface Pressure	0.0811	0.007	11.165	0.000	0.067	0.095	
Omnibus:	159.815 Durbin-Watson:		atson:		0.180		
Prob(Omnibus):	0.000 Jarque-B		era (JB):		237.960		
Skew:	-0.178			2.13e-52			
Kurtosis:	3.666	Cond. No			6.74e+08		

Warnings:

- [1] Standard Errors assume that the covariance matrix of the errors is correctly specified.
- [2] The condition number is large, 6.74e+08. This might indicate that there are strong multicollinearity or other numerical problems.