Report :

Introduction :

This dataset contains

This dataset contains records of simulation crashes encountered during climate model uncertainty. A total of 18 model parameters were used. A brief overview Class climate models are subject to fail or crash for a variety of reasons. Quantitative analysis of the failures can yield useful insights to better understand and improve the models. A climatic model can fail due to various factors, and there was a study done by the author who applied `SVM` to predict the probabilities of the crashes by using the below parameters.

What I've trying doing my analysis is to find the relavant features whcih could be more useful in predicting the climate change. I've used various models for comaprison and trying to find the best. I purposefully didn't used SVM here as it has been used in other study published.

The causes of the simulation failures were determined through a global sensitivity analysis. Combinations of 8 parameters related to ocean mixing and viscosity from three different POP2 parameterizations were the major sources of the failures. This information can be used to improve POP2 and CCSM4 by incorporating correlations across the relevant parameters. Our method can also be used to quantify, predict, and understand simulation crashes in other complex geoscientific models.

Attributes used :

Variables	Description
vconst_corr	variable viscosity parameter
vconst 2	variable viscosity parameter
vconst_3	variable viscosity parameter
vconst_4	variable viscosity parameter
vconst_5	variable viscosity parameter
vconst_7	variable viscosity parameter
ah_corr	diffusion coefficient for Redi mixing (ah) and background horizontal diffusivity within the surface boundary layer (ah bkg srfbl)
ah_bolus	diffusion coefficient for bolus mixing
slm_corr	maximum slope for bolus (slm b) and Redi terms (slm r)
efficiency_factor	efficiency factor for submesoscale eddies
tidal*mix*max	tidal mixing threshold
vertical*decay*scale	vertical decay scale for tide induced turbulence
convect_corr	tracer (convect diff) and momentum (convect visc)mixing coefficients in diffusion option
bckgrnd_vdc1	base background vertical diffusivity
bckgrnd*vdc*ban	Banda Sea diffusivity
bckgrnd*vdc*eq	equatorial diffusivity
bckgrnd*vdc*psim	maximum PSI induced diffusivity
Prandtl	ratio of background vertical viscosity and diffusivity
Outcome	0/1 Response variable

Total : 18 features were used y - Outcome Total count - 540

Step 1 Descriptive analysis

> - No missing values

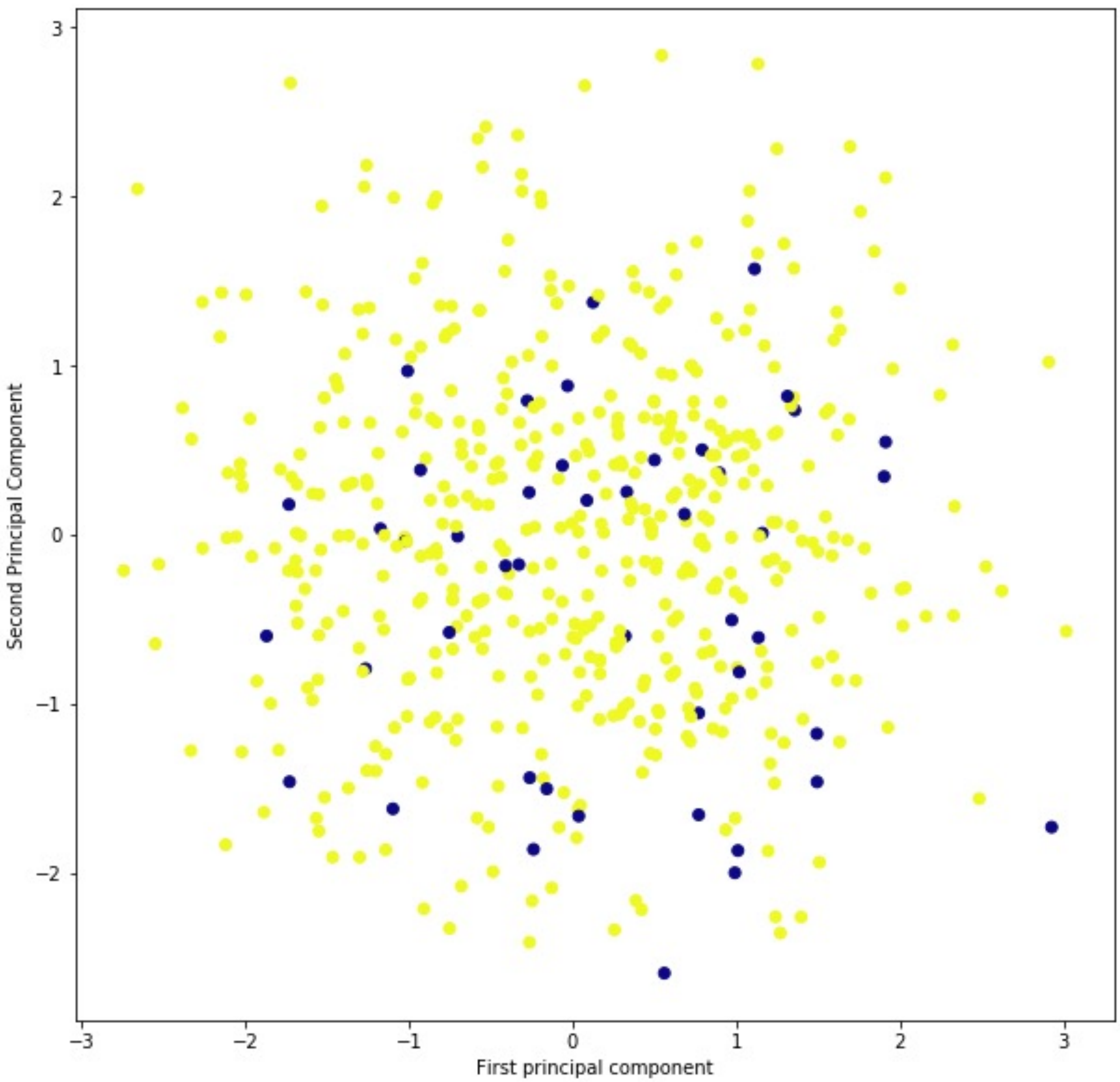
> - Data seem to be in standard scale

Step 2 Data Visualization

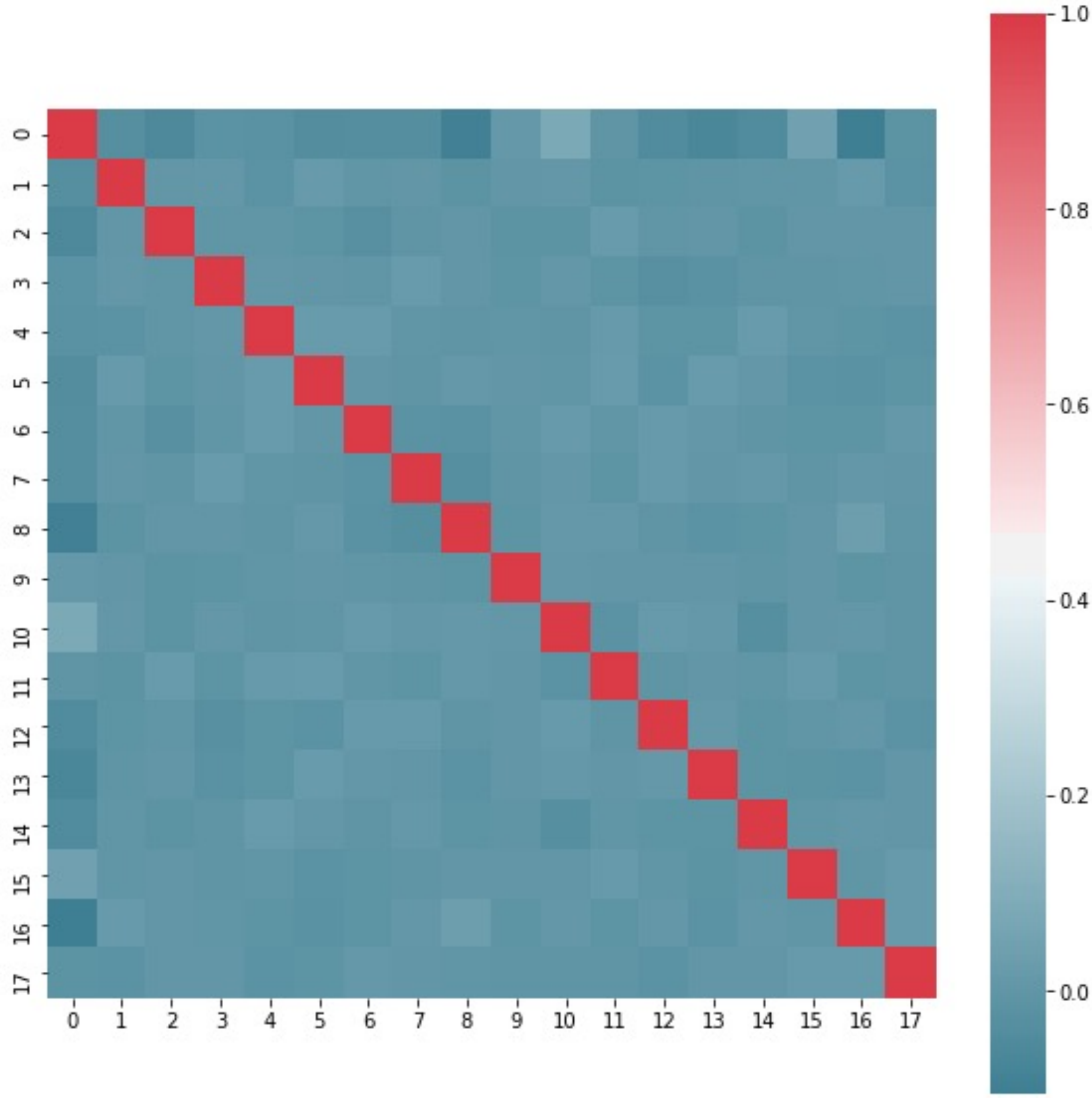
Since there are 18 features, and it wasn't possible to plot all of them. Selectively also I couldn't choose as this is a new domain for me. I decided to squish the variables into low dimension and use PCA instead for visualization purpose.

PCA

Visualizing 18 features into two features and representing in 2-d space.



Checking for correlation between the variables to check if that matters. Looks like figure above there is no high coorelation between two variables, it means predictors are good for predictions



Feature and model selection steps

1st Model

Firstly I decided to fit all the feaures on DT, just before I decide to run feature slection how good are features in terms of prediction. Results were very encouraging with DT as well. Got a test accuracy close to `90%` with all the features.

2nd Model

After fitting in DT, I decided to check how well Random forst will do on this model. With `100` estimators , accuracy went up to `92%` . Features were good predictors.

3rd Model feature selection

I decided to do cross validation on the model, even though first two runs on RF and DT proved almost all fetures are contributing towards prediction. USed three selection parameters by giving no of estimators to `n_estimators = [100,200,1000]` depth as `max_depth = [2,5,8,10]` and selection no of features as `max_features = [1,5,8,10,12,15]` . The results were encoraging with accuracy `0.948181` , and no of esitmators = `200.0` , with depth = `5` and most no of features `8` . This was encoraging. I wanted to try more models.

4th Model feature selection Logistic regression - no penalty

The results were good as expected, with accuracy close to `92%` and no of features selected will be `18` in this case.

5th Model feature selection Logistic regression - L1

This was the best results so fat with l1 so far with accuracy close to `95` and no of features selected were `13` . Most important this model was simple to be rolled out in production and interperability is easy.

Features selected from L1 : ['vconst*corr', 'vconst*2', 'vconst*3', 'vconst*5', 'vconst*7', 'ah*corr', 'ah*bolus', 'slm*corr', 'efficiency*factor', 'bckgrnd*vdc1', 'bckgrnd*vdc*ban', 'bckgrnd*vdc*psim', 'Prandtl']. In total `13` features.

6th Model feature selection Logistic regression - L2

Results of these were not as bad, accuracy was close to 93% with no of features close to 17.

7th Model feature selection logistic L1 Backward

The results of this was also very encouraging, with backwards selection criteria I was managed to get accuracy upto `95%` with `6` features. Couldnt extract the fatures to fit the model. Have to invetigate it further.

8th Model feature selection logistic L2 Backward

Results had a lot of randomnsess. I decided not to use this model. As the weights of the coefficients were vey high

9th Model feature selection Model 9 CV using L1 and L2 penealty

Mean square increased to `96%` for c `1.5` . It uses all the features. This is a good model for prediction.

sno	Model	TestAccuracy	h1	h2	features selected
1	DT	.903704			18
2	Random Forest	.9259	n_estimators=100		18
3	Cross Validation	.9481	n_estimators=200	dept= 5	8
4	Logistic no penalty	.9259			18
5	Logistic L1	.9481			13
6	Logistic L2	.9259			17
7	Logistic L1 + Backward	.948148			6
8	Logistic L2 + Backward	0.9333			4
9	Model 9 CV using L1 and L2 penealty	0.962996	c=1.5	cv=5 ,L1	18

Conclusion : I decided model 5, logistic regression was the best out of the models that I have tried. So I decided to give it a try I fitted both logistic regression and random forest in reduced no of features to see the performance. Please find below the code along with the results.

```
climate_data=pd.read_csv('climate.csv')

X_more = climate_data[["vconst_corr","vconst_2","vconst_3","vconst_5","vconst_7","ah_
corr",
          "ah_bolus","slm_corr","efficiency_factor","bckgrnd_vdc1","bckgrnd_vdc_ban",
"bckgrnd_vdc_psim","Prandtl"]]

y_more = climate_data['outcome'].values
# Splitting the dataset in 25% train and test

X_train, X_test, y_train, y_test = train_test_split(X_more, y_more, test_size=0.25)

#penalty l1
model_l1 = LogisticRegression()

# Fitting the model
model_l1.fit(X_train,y_train)
```

```
pred = model_l1.predict(X_test)

# coefficient calculation and error calculation

sf_model = np.sum(model_l1.coef_/max(model_l1.coef_) >= 1e-6)
v_error = np.mean(model_l1.predict(X_test) != y_test)

accuracy = np.mean(pred==y_test)
# printing the features, and error

print(' L1 regularization: no of features ', sf_model)
print(' L1 regularization: accuracy ', accuracy)


# random forest model

rfc = RandomForestClassifier(n_estimators=100)
rfc.fit(X_train, y_train)

rfc_pred = rfc.predict(X_test)
smse = sum(rfc_pred != y_test) / len(y_test)

Accuracy = 1-smse

#print('Test error = %f' % smse)
print('Accuracy = %f' % Accuracy)
print('Error = %f' % error)
error=1-Accuracy
```

```
Using logistic regression

L1 regularization: no of features  13
L1 regularization: accuracy  0.896296296296

Using Random forest

Accuracy = 0.903704
Error = 0.074074
```

[python notebook]

[Reference paper]

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