Project\_precipitation\_downscaling

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# 1. Overview

Precipitation is difficult to monitor and predict, whereas data on other environmental variables are relatively easy to obtain. There might be some correlation between these variables and precipitation. In this project, the goal is to develop a precipitation downscaling model using Principal Components Analysis (PCA) and K Nearest Neighbors (KNN) based on environmental variables such as temperature, geopotensial, and cloud cover fraction. The focus region is Houston, and the data utilized is obtained from ERA5 reanalysis.

# 2. Set up

# 3. Read data

ERA5 reanalysis data for temperature, pressure, and cloud cover fraction were collected for the Houston region. The data spanned a specific time period from 1979 to 2022, where longitude ranges from 258.25 to 269.25 and latitude from 25.25 to 36.25. Precipitation is obtained from NEXRAD radar precipitation data. For this project, I used the same precipitation data from lab 6. One thing to note is that the latitude data is flipped, so we need to rearrange it in the proper order. We also need to repeat this process for the other variables.

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 0.0 0.0 0.0 0.0 0.00781286 0.0390643  
 0.0 0.0 0.0156257 0.00781286 0.0 0.0  
 0.0 0.0 0.0156257 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.00781286 0.0 0.0  
 0.0 0.0 0.0 0.0234386 0.0 0.0  
 0.0 0.0 0.0 0.0 0.00781286 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.257809 0.523431 0.00781286  
  
[:, :, 2] =  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0156257 0.0 0.0 0.0 0.0 0.0  
 0.0 0.00781286 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0390643 0.0156257 0.0468771 … 0.0 0.0 0.0 0.0 0.0  
 0.0156257 0.0859414 0.0859414 0.0234386 0.0 0.0 0.0 0.0  
  
[:, :, 3] =  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
  
;;; …   
  
[:, :, 16069] =  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
  
[:, :, 16070] =  
 0.0234386 0.351563 0.132819 … 0.0 0.0 0.0  
 0.0 0.0468771 0.0156257 0.0 0.0 0.0  
 0.0 0.0 0.367189 0.0 0.0 0.0  
 0.0 0.0 0.0859414 0.0 0.0 0.0  
 0.0 0.0 0.0 0.328125 0.0 0.0  
 0.0 0.0 0.0 … 0.898433 0.171868 0.0  
 0.0 0.0 0.0156257 0.0859414 0.874994 0.00781286  
 0.0 0.0234386 0.0312514 0.00781286 0.0859414 0.406253  
 0.00781286 0.0 0.0 0.0390643 0.0 0.218745  
 0.0156257 0.0234386 0.0234386 0.00781286 0.00781286 0.132819  
 0.0 0.0156257 0.0 … 0.0312514 0.0 0.0156257  
 0.0312514 0.00781286 0.0 0.0234386 0.140631 0.23437  
  
[:, :, 16071] =  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0156257 0.0 0.0 0.0  
 0.0 0.0 0.0 0.335938 0.0156257 0.0 0.0  
 0.0 0.0 0.0 0.742191 0.132819 0.0 0.0  
 0.0 0.0 0.0 … 0.750004 0.54687 0.0 0.0  
 0.0 0.0 0.0 0.898433 0.882807 0.10938 0.0  
 0.0 0.0 0.0 1.0 0.929684 0.101567 0.0  
 0.0 0.0 0.0 0.0 0.156257 0.0 0.0  
 0.0312514 0.17968 0.0703157 0.0 0.0312514 0.0 0.0  
 0.0468771 0.0234386 0.0859414 … 0.226558 0.0781286 0.0 0.0  
 0.0156257 0.0234386 0.0625029 0.0 0.101567 0.0 0.0

# 4. Plot heatmap for a single day

In this section, I wanted to get a general idea of the correlation between these variables and precipitation, so I picked a random day and plotted a heat map for each variable separately. I found temperature and geopotential to be very consistent, but they don’t seem to have much to do with precipitation. However, cloud cover seems to have some relationship with rainfall, which makes sense because generally speaking, the more clouds in the sky, the greater the likelihood of rain.

# 5. Split the data

This downscaling model was trained on the training set and validated on the testing set. I splited the training set and the testing set based on the timeline. The data from last five years was catagoried into testing set while the rest of the data served as training set.

12×12×1826 Array{Union{Missing, Float64}, 3}:  
[:, :, 1] =  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.101567 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.00781286 0.00781286 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
  
[:, :, 2] =  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0859414 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0390643 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0156257 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.16407 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0156257 0.359376 0.0234386 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0234386 0.898433 0.304686 0.0 0.0 0.0 0.0 0.0 0.0  
 0.148444 0.10938 0.257809 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0859414 0.0 0.171868 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0312514 0.0 0.0156257 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0312514 0.0 … 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.00781286 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
  
[:, :, 3] =  
 0.0 0.0 0.0 0.0 … 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 … 0.0312514 0.0 0.0  
 0.0 0.0 0.0 0.0 0.671875 0.0 0.0  
 0.0 0.0 0.0 0.0 0.859369 0.367189 0.0  
 0.0156257 0.0 0.0 0.0 0.82032 0.562495 0.94531  
 0.00781286 0.0 0.00781286 0.00781286 0.82032 0.83593 0.953123  
 0.0 0.0 0.0625029 0.00781286 … 0.757817 0.789068 0.960936  
 0.0 0.0 0.187493 0.0156257 0.328125 0.882807 0.976561  
  
;;; …   
  
[:, :, 1824] =  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
  
[:, :, 1825] =  
 0.0234386 0.351563 0.132819 … 0.0 0.0 0.0  
 0.0 0.0468771 0.0156257 0.0 0.0 0.0  
 0.0 0.0 0.367189 0.0 0.0 0.0  
 0.0 0.0 0.0859414 0.0 0.0 0.0  
 0.0 0.0 0.0 0.328125 0.0 0.0  
 0.0 0.0 0.0 … 0.898433 0.171868 0.0  
 0.0 0.0 0.0156257 0.0859414 0.874994 0.00781286  
 0.0 0.0234386 0.0312514 0.00781286 0.0859414 0.406253  
 0.00781286 0.0 0.0 0.0390643 0.0 0.218745  
 0.0156257 0.0234386 0.0234386 0.00781286 0.00781286 0.132819  
 0.0 0.0156257 0.0 … 0.0312514 0.0 0.0156257  
 0.0312514 0.00781286 0.0 0.0234386 0.140631 0.23437  
  
[:, :, 1826] =  
 0.0 0.0 0.0 … 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0 0.0 0.0 0.0  
 0.0 0.0 0.0 0.0156257 0.0 0.0 0.0  
 0.0 0.0 0.0 0.335938 0.0156257 0.0 0.0  
 0.0 0.0 0.0 0.742191 0.132819 0.0 0.0  
 0.0 0.0 0.0 … 0.750004 0.54687 0.0 0.0  
 0.0 0.0 0.0 0.898433 0.882807 0.10938 0.0  
 0.0 0.0 0.0 1.0 0.929684 0.101567 0.0  
 0.0 0.0 0.0 0.0 0.156257 0.0 0.0  
 0.0312514 0.17968 0.0703157 0.0 0.0312514 0.0 0.0  
 0.0468771 0.0234386 0.0859414 … 0.226558 0.0781286 0.0 0.0  
 0.0156257 0.0234386 0.0625029 0.0 0.101567 0.0 0.0

# 6. Preprocess

The purpose of preprocessing the data is to obtain variance data and reshape these variance data arrays into matrix for the next step.

144×1826 Matrix{Float64}:  
 -0.0469915 -0.0469915 -0.0469915 … -0.0235529 -0.0469915  
 -0.05044 0.0355015 -0.05044 -0.05044 -0.05044  
 -0.0326624 -0.00141094 -0.0404752 -0.0404752 -0.0404752  
 -0.0308869 -0.0152612 -0.0308869 -0.0308869 -0.0308869  
 -0.0207038 -0.0207038 -0.0207038 -0.0207038 -0.0207038  
 -0.0195914 -0.00396564 -0.0195914 … -0.0195914 -0.0195914  
 -0.0150989 0.00833966 -0.0150989 -0.0150989 -0.0150989  
 -0.0170242 0.13142 -0.0170242 -0.0170242 -0.0170242  
 -0.0177944 0.068147 -0.00216868 -0.00998154 -0.0177944  
 -0.0175763 0.0136752 -0.00976341 -0.00195055 0.0136752  
 -0.0200107 -0.0200107 -0.0200107 … -0.0200107 0.0268665  
 -0.0219488 -0.0219488 -0.0219488 0.00930265 -0.00632307  
 -0.0423533 -0.0423533 -0.0423533 0.30921 -0.0423533  
 ⋮ ⋱ ⋮  
 -0.0412408 -0.0412408 -0.0412408 -0.0412408 -0.0412408  
 -0.0367954 -0.0367954 -0.0367954 -0.0367954 -0.0367954  
 -0.0294876 -0.0294876 -0.0294876 -0.0294876 -0.0294876  
 -0.0319819 -0.0319819 -0.0319819 … -0.0319819 -0.0319819  
 -0.0385409 -0.0385409 -0.0385409 -0.0385409 -0.0385409  
 -0.0424727 -0.0424727 -0.0424727 -0.0424727 -0.0424727  
 -0.0444878 -0.0444878 -0.0444878 -0.036675 -0.0444878  
 -0.0434226 -0.0434226 -0.0434226 0.362831 -0.0434226  
 -0.0490959 -0.0490959 0.896214 … 0.169649 -0.0490959  
 -0.0518041 -0.0518041 0.901319 0.0810145 -0.0518041  
 -0.0565018 -0.0565018 0.904434 -0.0408761 -0.0565018  
 -0.0662226 -0.0662226 0.910339 0.168148 -0.0662226

# 7. Principal components analysis

PCA was employed in this model to reduce the dimensionality of the input data while preserving essential information. This method is beneficial for capturing dominant patterns in the variables. The number of principal components selected was determined through analysis of the explained variance. Here I plotted the explained variance and cumulative explained variance for all three variables. From these plots we can see that for the temperature and geopotential data we can get most of the information by choosing only two principal components, but for the cloud cover data, two principal components are not enough.

We can also plot the projection of these PCs on the latitude and longitude axes.

For this part, I plotted the time series of the first two PCs. The results are consistent with my speculation above. Based on these graphs, I hypothesize that PC 1 varies seasonally, while PC 2 and PC 3 are more closely related to daily variations. In addition, the PCs of temperature and geopotential data have very similar patterns which means they are closely related.

These are scatter plots of rainfall for each variables. We have assumed that rainy days have precipitation values above the 98th percentile.

# 8. K nearest neighbors

Here we created a function of the KNN algorithm. The KNN algorithm was trained on the PCA-transformed data, associating each point with its high-resolution precipitation value. K is the hyperparameter of the algorithm, which we set to a number before running the function. We use Euclidean distance as the distance metric. We select the K data points that are closest to the point we want to predict, and the data point with the smallest distance has the highest weight.

knn (generic function with 1 method)

And then we combine PCA and KNN together

predict\_knn (generic function with 1 method)

# 9. Prediction results

Now we can feed the data into the model we just built and plot heat maps of the predicted results and the actual rainfall data. What I have done here is to randomly select three days from the test set and compare the rainfall predictions with the actual rainfall data. I found that the rainfall predictions based on temperature and potential data were not as good as expected. However, the predictions based on cloud cover were sometimes closer to the actual rainfall.

# 10. Conclusion

In summary, the differences in model performance based on different input variables highlight the complexity of precipitation patterns. The rainfall prediction based on cloud cover fraction offers a promising avenue for future research and model refinement. There are other potential variables related to rainfall, such as specific humidity, so it may be helpful if we can incorporate more variables. In addition, we could use other models such as random forests and generalized linear regression models which might provide a better prediction.