# Perform PCA for Dimensions 1 to 10 of Chile’s Tourism Regions

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# Roadmap

Data Cleaning → PCA → Recommendation

# Data Cleaning

1. Delete first <u>6 empty rows</u> of the Excel data file
2. Save the data file as csv file
3. Read the csv file by Python

| Regions | Density of restaurants per 100,000 habitants | People working at restaurants per 10,000 habitants | Car r |
|---|---|---|---|
| Arica y Parinacota (XV) | 35.857 | 19.563 | |
| Tarapacá (I) | 25.947 | 26.616 | |
| Antofagasta (II) | 37.248 | 35.446 | |
| Atacama (III) | 44.823 | 26.933 | |
| Coquimbo (IV) | 37.632 | 25.165 | |
| Valparaíso (V) | 52.408 | 47.050 | |
| Metropolitana (RM) | 9.223 | 16.914 | |
| O'Higgins (VI) | 18.959 | 49.422 | |
| Maule (VII) | 15.637 | 19.943 | |
| Biobío (VIII) | 14.128 | 14.004 | |
| Araucanía (IX) | 15.986 | 15.687 | |
| Los Ríos (XIV) | 34.512 | 26.207 | |
| Los Lagos (X) | 36.415 | 27.360 | |
| Aysén (XI) | 76.509 | 40.987 | |

# Data Cleaning

4. Remove useless rows

5. Rename the first column that represents regions and make sure the names of regions are the same as those from dim1 to dim 6 so that combining the PCA results in the end will be easy.

```
# Remove last rows - from 16 to 18
chile_data_2 = chile_data_2[:-4]
```

```
# Rename the first column
chile_data_2 = chile_data_2.rename(columns={'Regions': 'Region'})
```

```
chile_data_2
```

| | Region | Density of restaurants per 100,000 habitants | People working at restaurants per 10,000 habitants | Car rental agencies | Hospital beds per 10,000 habitants | Density of ATM machines per 100,000 habitants | Spas | Ca 1( hab |
|---|---|---|---|---|---|---|---|---|
| 0 | Arica y Parinacota | 35.857 | 19.563 | 12 | 21.619 | 43.766 | 0 | |
| 1 | Tarapac¨¢ | 25.947 | 26.616 | 2 | 18.958 | 60.264 | 0 | |
| 2 | Antofagasta | 37.248 | 35.446 | 22 | 29.96 | 69.233 | 3 | |
| 3 | Atacama | 44.823 | 26.933 | 19 | 25.478 | 56.225 | 1 | |
| 4 | Coquimbo | 37.632 | 25.165 | 9 | 17.805 | 47.745 | 3 | |
| 5 | Valpara¨ªso | 52.408 | 47.05 | 16 | 27.756 | 55.85 | 9 | |
| 6 | Metropolitana | 9.223 | 16.914 | 47 | 25.508 | 65.499 | 0 | |

# Data Cleaning

6. Remove extra symbols

```
# Remove $ symbol
chile_data_2 = chile_data_2.replace(r'[<$]', '', regex = True)
# Remove commas from numbers
chile_data_2 = chile_data_2.replace(',','', regex = True)
# Remove `-` character
chile_data_2 = chile_data_2.replace('-','', regex = True)
# Replace empty values with NaNs
chile_data_2 = chile_data_2.replace(r'^\s*$', np.nan, regex = True)
# Check NaNs in the dataset again
chile_data_2
```

7. Delete columns in which 30% ~ 70% of the variables are NaNs.

```
# Drop 4 columns with many NaNs
chile_data_2 = chile_data_2 = chile_data_2.drop(['Ski resorts',
                                                 'Major shopping centers',
                                                 'Number of vineyards',
                                                 'Governmental resources a
```

8. Unlist columns

```
# Impute data in four columns
imputer = SimpleImputer(missing_values = n
chile_data_2[['Crime index',
              'Illegal commerce',
              'Seed funds allocated to the tourism sector ($)',
              'Yearly budget for international tourism promotion ($M
              'Illegal commerce',
              'Seed funds allocated to the tourism sector ($)',
              'Yearly budget for international tourism promotion ($M
```

```
# Setting index
chile_data_2 = chile_data_2.set_index('Region')

# Select columns
cols = chile_data_2.loc[:, chile_data_2.dtypes == np.object].column

# Convert to numeric
chile_data_2[cols] = chile_data_2[cols].apply(pd.to_numeric, errors

# Now all our columns are integers or floats
chile_data_2 = chile_data_2.reset_index()
```

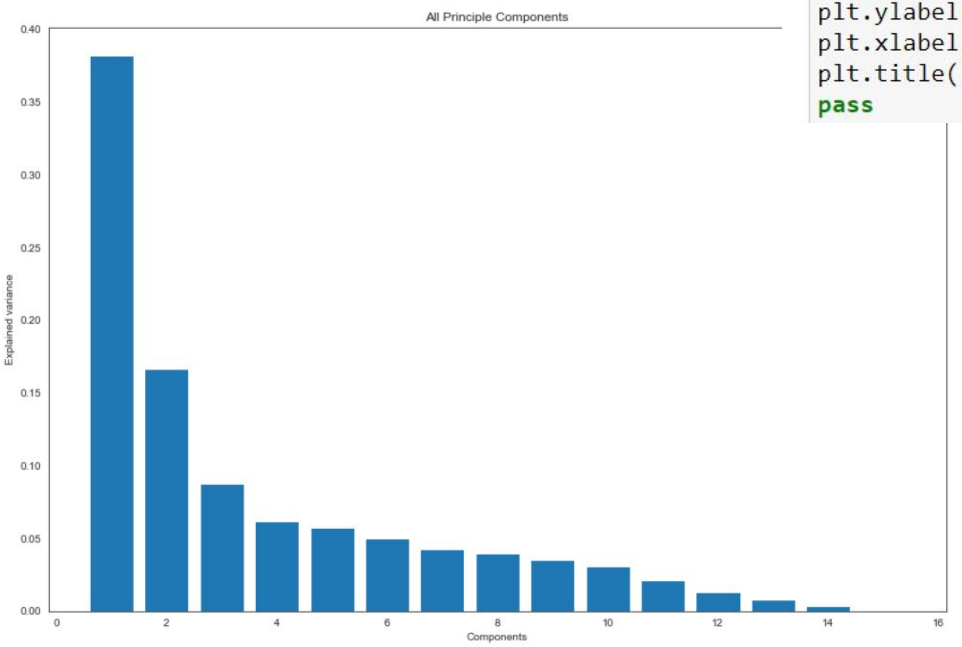
# Standardize data for applying PCA

```
# Create a copy
chile_data_s_2 = chile_data_2.copy()

# Standardize
scaler = StandardScaler()
chile_data_s_2.loc[:, chile_data_s_2.columns != 'Region'] = scaler.fit_transform(chile_data_s_2.loc[:,
                                                            chile_data_s_2.columns != 'Region'])

# Set region as an index column
chile_data_s_2 = chile_data_s_2.set_index('Region')
pass
```

# PCA

1. Eigenvalues & Eigenvectors
2. Run PCA and fit the model

```python
# Run PCA and fit the model
myPCA = PCA()
x = myPCA.fit(chile_data_s_2)

# Plotting the variance explained by each component
plt.bar(range(1,len(x.explained_variance_ )+1),x.explained_variance_ratio_)
plt.ylabel('Explained variance')
plt.xlabel('Components')
plt.title('All Principle Components')
pass
```




3. Plot the variance explained by each component

# PCA

3. Explore the importance of each feature for principle components

4. Calculate factor scores

```
pca_model = myPCA.fit_transform(chile_data_s_2)
PCcomponents = pd.DataFrame(data = pca_model, columns = ['PC1', 'PC2', 'PC3', 'PC4', 'PC5', 'PC6', 'PC7'])
print("\n The Factor scores are")
PCcomponents
```

The Factor scores are

| | PC1 | PC2 | PC3 | PC4 | PC5 | PC6 | PC7 |
|---|---|---|---|---|---|---|---|
| **0** | -2.373870 | 0.823256 | 0.472329 | -2.079397 | -2.919301 | 0.141580 | 0.186033 |
| **1** | -1.485061 | -0.247090 | 6.228244 | -2.115655 | 1.203540 | 0.595868 | 0.757801 |
| **2** | 0.263871 | 2.084163 | 1.119329 | 4.384186 | 0.480078 | 3.195863 | 0.422146 |
| **3** | -1.814625 | 0.019734 | 2.139679 | 2.229493 | -0.772417 | -1.927273 | -0.772461 |
| **4** | -0.969405 | -1.998904 | -0.011820 | 0.458845 | 1.718456 | -1.177366 | -1.155089 |
| **5** | 1.188020 | 0.340730 | -0.711721 | -0.291174 | -0.750611 | 1.368108 | 0.495793 |
| **6** | 14.460293 | 2.855751 | 0.166888 | -0.525576 | -0.548933 | -0.744969 | -0.624666 |
| **7** | -1.283626 | -0.937935 | -0.789281 | -1.051599 | -2.088445 | 1.379180 | -1.114501 |
| **8** | -0.680583 | -3.431526 | -0.366983 | -0.213786 | -1.694869 | -0.554999 | -0.381959 |
| **9** | 2.024578 | -3.385638 | -1.595265 | -1.373500 | 2.088322 | 0.846775 | 3.060953 |
| **10** | 0.412162 | -4.107222 | -0.063790 | 1.987826 | -0.289221 | -2.512417 | 0.329350 |
| **11** | -1.888205 | -1.361590 | -2.279907 | 0.261054 | -1.076617 | 1.509792 | -0.109209 |
| **12** | 0.031550 | -0.800397 | -1.746730 | -0.594429 | 3.044853 | -0.001577 | -1.242050 |
| **13** | -3.898966 | 3.945054 | -0.990212 | -1.273527 | 1.729195 | 0.068358 | -2.559529 |
| **14** | -3.986135 | 6.201613 | -1.570759 | 0.197240 | -0.124031 | -2.186923 | 2.707388 |

```
pca = PCA(n_components = 7).fit(chile_data_s_2)
vars = pca.explained_variance_ratio_
c_names = chile_data_s_2.columns
sum = 0

print('Variance:  Projected dimension')
print('------------------------------')
for idx, row in enumerate(pca.components_):
    output = '{0:4.1f}%:    '.format(100.0 * vars[idx])
    output += " + ".join("{0:5.2f} * {1:s}".format(val, name) \
                      for val, name in zip(row, c_names))
    sum += 100*vars[idx]
    print(output)

print('Total variance explained by the 7 components {0:4.1f}%'.format(sum))
# Total variance explained by the 7 components 84.8.0%
```

# PCA

5. Fit the model

6. Compute weights

```
myPCA = PCA(n_components = 7)
pca_model = myPCA.fit(chile_data_s_2)
y_axis = [0,0,0,0,0,0,0]
for i in range(0,7):
    y_axis[i]=[np.mean(pca_model.components_[i][0:15]), np.mean(pca_model.c
               np.mean(pca_model.components_[i][27:36]), np.mean(pca_model.
               np.mean(pca_model.components_[i][41:46])]
# Plot
x_axis = ['TOURISM-RELATED SERVICES', 'SECURITY AND SAFETY ', 'ECONOMIC PER
plt.plot(x_axis,y_axis[0], color = 'mediumaquamarine', label = "C1")
plt.plot(x_axis,y_axis[1], color = 'yellow', label = "C2")
plt.plot(x_axis,y_axis[2], color = 'pink', label = "C3")
plt.plot(x_axis,y_axis[3], color = 'steelblue', label = "C4")
plt.plot(x_axis,y_axis[4], color = 'salmon', label = "C5")
plt.plot(x_axis,y_axis[5], color = 'red', label = "C6")
plt.plot(x_axis,y_axis[6], color = 'orange', label = "C7")
plt.xticks(rotation = 90)
plt.title('Example of variable contributions to each principal component')
plt.legend()
pass
```

```
# Creating a dataframe of weights
weights = pd.DataFrame(np.column_stack((chile_data_s_2.columns, pca_model.components_[0] *
                                        pca_model.explained_variance_ratio_[0],
                                        pca_model.components_[1] * pca_model.explained_variance_ratio_[1],
                                        pca_model.components_[2] * pca_model.explained_variance_ratio_[2],
                                        pca_model.components_[3] * pca_model.explained_variance_ratio_[3],
                                        pca_model.components_[4] * pca_model.explained_variance_ratio_[4],
                                        pca_model.components_[5] * pca_model.explained_variance_ratio_[5],
                                        pca_model.components_[6] * pca_model.explained_variance_ratio_[6]))
weights = weights.set_index(0)

# Create a weighted average
weights['weighted_average'] = weights.sum(axis = 1)/np.sum(pca_model.explained_variance_ratio_)

# Print
weights.head()
```

| 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | weighted_average |
|---|---|---|---|---|---|---|---|---|
| Density of restaurants per 100,000 habitants | -0.0508779 | 0.0383434 | -0.00603016 | 0.00173496 | 0.00703431 | -0.000705732 | -0.00638432 | -0.019904 |
| People working at restaurants per 10,000 habitants | -0.0371438 | 0.0379041 | -0.00768655 | 0.00145828 | -0.00263994 | 0.00488203 | 0.000651091 | -0.003035 |
| Car rental agencies | 0.0748317 | 0.0115487 | -0.0072556 | 0.0104844 | 0.00355798 | -0.00633721 | -0.00327852 | 0.098485 |
| Hospital beds per 10,000 habitants | -0.00384581 | 0.0285705 | -0.0193489 | 0.0143164 | -0.00104324 | 0.00105819 | 0.0132646 | 0.038865 |
| Density of ATM machines per 100,000 habitants | 0.0220336 | 0.0438976 | 0.0153522 | 0.0128237 | 0.00260291 | 0.000892908 | 0.0075618 | 0.123961 |

# PCA

```
# Ranking for dimension 6: TOURISM-RELATED SERVICES

# Create a dataframe for relevant variables
dim6 = chile_data_s_2.iloc[:, 0:15].mul(weights['weighted_average'][0:15], axis = 1)

# Create a score ranking
dim6['Ranking 6'] = dim6.sum(axis = 1)

# Sort by score
dim6.sort_values(by = 'Ranking 6', ascending = False)
```

7. Create a score ranking for dim 6

8. Compute ranks for dim 7 to 10 in the same way

9. Combine all 5 ranks

| Region | Ranking 6 | Ranking 7 | Ranking 8 | Ranking 9 | Ranking 10 |
|---|---|---|---|---|---|
| Arica y Parinacota | -0.219562 | -0.431607 | -0.218964 | -0.127449 | -0.193358 |
| Tarapac¨¢ | -0.139428 | 0.184253 | 0.111514 | -0.033586 | -0.196716 |
| Antofagasta | 0.367888 | 0.126460 | 0.436016 | 0.197444 | 0.076666 |
| Atacama | -0.059748 | -0.323617 | -0.149980 | 0.054979 | -0.156984 |
| Coquimbo | -0.327888 | -0.296003 | -0.271570 | 0.128133 | -0.040475 |
| Valpara¨ªso | 0.339170 | 0.177603 | 0.047514 | -0.061269 | 0.058999 |
| Metropolitana | 1.793741 | 2.208516 | 1.618444 | 0.672550 | 0.647190 |
| O'Higgins | -0.319237 | -0.415101 | -0.064561 | -0.184920 | -0.053559 |
| Maule | -0.494721 | -0.279228 | -0.305912 | -0.114380 | -0.006079 |
| Biob¨ªo | -0.044464 | 0.453489 | -0.071235 | -0.087292 | 0.079230 |
| Araucan¨ªa | -0.402073 | 0.026774 | -0.323501 | 0.013958 | 0.052154 |
| Los R¨ªos | -0.381948 | -0.423620 | -0.316565 | -0.131099 | -0.070488 |
| Los Lagos | -0.127404 | -0.209206 | -0.038840 | -0.032185 | 0.184970 |
| Ays¨¦n | -0.302594 | -0.322888 | -0.210162 | -0.088698 | -0.261150 |
| Magallanes y Ant¨¢rtica | 0.318268 | -0.475825 | -0.242200 | -0.206185 | -0.120398 |

## 10. Combine the ranks for Dimensions 1 to 10

```
final_scoring_data = pd.concat([dim1.iloc[:,-1:], dim2.iloc[:,-1:], dim3.iloc[:,-1:], dim4.iloc[:,-1:], dim5.iloc[:,-1:]
                                ,dim6.iloc[:,-1:], dim7.iloc[:,-1:], dim8.iloc[:,-1:], dim9.iloc[:,-1:],
                              dim10.iloc[:,-1:]], axis = 1)
final_scoring_data
```

| Region | Ranking 1 | Ranking 2 | Ranking 3 | Ranking 4 | Ranking 5 | Ranking 6 | Ranking 7 | Ranking 8 | Ranking 9 | Ranking 10 |
|---|---|---|---|---|---|---|---|---|---|---|
| Arica y Parinacota | -0.415952 | 0.084054 | -0.227440 | -0.142092 | 0.074729 | -0.219562 | -0.431607 | -0.218964 | -0.127449 | -0.193358 |
| Tarapac¨¢ | -0.173136 | -0.013629 | -0.063857 | -0.051780 | -0.111462 | -0.139428 | 0.184253 | 0.111514 | -0.033586 | -0.196716 |
| Antofagasta | -0.023722 | -0.210598 | -0.075573 | 0.003949 | -0.066772 | 0.367888 | 0.126460 | 0.436016 | 0.197444 | 0.076666 |
| Atacama | -0.315089 | -0.340057 | -0.188900 | -0.203309 | -0.415831 | -0.059748 | -0.323617 | -0.149980 | 0.054979 | -0.156984 |
| Coquimbo | -0.250916 | 0.091873 | -0.128560 | 0.049329 | -0.217581 | -0.327888 | -0.296003 | -0.271570 | 0.128133 | -0.040475 |
| Valpara¨ªso | 0.692363 | 0.174514 | 0.249814 | 0.405196 | 0.380127 | 0.339170 | 0.177603 | 0.047514 | -0.061269 | 0.058999 |
| Metropolitana | 2.505190 | 0.512320 | 1.245244 | 1.013256 | 1.231514 | 1.793741 | 2.208516 | 1.618444 | 0.672550 | 0.647190 |
| O'Higgins | -0.571647 | -0.122728 | -0.138538 | -0.318736 | -0.295041 | -0.319237 | -0.415101 | -0.064561 | -0.184920 | -0.053559 |
| Maule | -0.476902 | -0.145830 | -0.227193 | -0.242213 | -0.240416 | -0.494721 | -0.279228 | -0.305912 | -0.114380 | -0.006079 |
| Biob¨ªo | 0.312954 | -0.259354 | 0.138733 | -0.096586 | 0.019311 | -0.044464 | 0.453489 | -0.071235 | -0.087292 | 0.079230 |
| Araucan¨ªa | -0.510915 | -0.330403 | -0.159923 | 0.004307 | -0.067661 | -0.402073 | 0.026774 | -0.323501 | 0.013958 | 0.052154 |
| Los R¨ªos | -0.294472 | 0.045124 | -0.245964 | -0.086307 | -0.333723 | -0.381948 | -0.423620 | -0.316565 | -0.131099 | -0.070488 |
| Los Lagos | 0.204969 | 0.577425 | 0.254603 | 0.254766 | 0.565572 | -0.127404 | -0.209206 | -0.038840 | -0.032185 | 0.184970 |
| Ays¨¦n | -0.441574 | -0.012318 | -0.253732 | -0.422402 | -0.465189 | -0.302594 | -0.322888 | -0.210162 | -0.088698 | -0.261150 |
| Magallanes y Ant¨¢rtica | -0.241153 | -0.050395 | -0.178714 | -0.167379 | -0.057579 | 0.318268 | -0.475825 | -0.242200 | -0.206185 | -0.120398 |

# PCA

11. Calculate the overall tourism competitiveness ranking for all regions

```
final_scoring_data["Overall Ranking Score"] = final_scoring_data.sum(axis = 1)
```

```
final_scoring_data['Overall Ranking'] = final_scoring_data['Overall Ranking Score'].rank(ascending=False)
```

# PCA

12. highlight dataframe values with colors

```python
# attach CSS classes to each cell
final_scoring_data.style.highlight_null().render().split('\n')[:10]

# Create a function for negative values (red)
def color_negative_red(val):
    """
    Takes a scalar and returns a string with
    the css property `'color: red'` for negative
    strings, black otherwise.
    """
    color = 'red' if val < 0 else 'black'
    return 'color: %s' % color

# Create a function for max values (yellow)
def highlight_max(s):
    '''
    highlight the maximum in a Series yellow.
    '''
    is_max = s == s.max()
    return ['background-color: yellow' if v else '' for v in is_max]

# Apply styles
final_scoring_data.style.\
    applymap(color_negative_red).\
    apply(highlight_max)
```

| Region | Ranking 1 | Ranking 2 | Ranking 3 | Ranking 4 | Ranking 5 | Ranking 6 | Ranking 7 | Ranking 8 | Ranking 9 | Ranking 10 | Overall Ranking Score | Overall Ranking |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Arica y Parinacota | -0.415952 | 0.084054 | -0.227440 | -0.142092 | 0.074729 | -0.219562 | -0.431607 | -0.218964 | -0.127449 | -0.193358 | -1.817640 | 10.000000 |
| Tarapac¨¢ | -0.173136 | -0.013629 | -0.063857 | -0.051780 | -0.111462 | -0.139428 | 0.184253 | 0.111514 | -0.033586 | -0.196716 | -0.487826 | 6.000000 |
| Antofagasta | -0.023722 | -0.210598 | -0.075573 | 0.003949 | -0.066772 | 0.367888 | 0.126460 | 0.436016 | 0.197444 | 0.076666 | 0.831759 | 4.000000 |
| Atacama | -0.315089 | -0.340057 | -0.188900 | -0.203309 | -0.415831 | -0.059748 | -0.323617 | -0.149980 | 0.054979 | -0.156984 | -2.098536 | 11.000000 |
| Coquimbo | -0.250916 | 0.091873 | -0.128560 | 0.049329 | -0.217581 | -0.327888 | -0.296003 | -0.271570 | 0.128133 | -0.040475 | -1.263659 | 7.000000 |
| Valpara¨ªso | 0.692363 | 0.174514 | 0.249814 | 0.405196 | 0.380127 | 0.339170 | 0.177603 | 0.047514 | -0.061269 | 0.058999 | 2.464031 | 2.000000 |
| Metropolitana | 2.505190 | 0.512320 | 1.245244 | 1.013256 | 1.231514 | 1.793741 | 2.208516 | 1.618444 | 0.672550 | 0.647190 | 13.447966 | 1.000000 |
| O'Higgins | -0.571647 | -0.122728 | -0.138538 | -0.318736 | -0.295041 | -0.319237 | -0.415101 | -0.064561 | -0.184920 | -0.053559 | -2.484068 | 13.000000 |
| Maule | -0.476902 | -0.145830 | -0.227193 | -0.242213 | -0.240416 | -0.494721 | -0.279228 | -0.305912 | -0.114380 | -0.006079 | -2.532874 | 14.000000 |
| Biob¨ªo | 0.312954 | -0.259354 | 0.138733 | -0.096586 | 0.019311 | -0.044464 | 0.453489 | -0.071235 | -0.087292 | 0.079230 | 0.444784 | 5.000000 |

# PCA

13. Sort the overall tourism competitiveness ranking for all regions

```
final_scoring_data.sort_values(by='Overall Ranking Score', ascending=False)
```

| Region | Ranking 1 | Ranking 2 | Ranking 3 | Ranking 4 | Ranking 5 | Ranking 6 | Ranking 7 | Ranking 8 | Ranking 9 | Ranking 10 | Overall Ranking Score | Overall Ranking |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Metropolitana | 2.505190 | 0.512320 | 1.245244 | 1.013256 | 1.231514 | 1.793741 | 2.208516 | 1.618444 | 0.672550 | 0.647190 | 13.447966 | 1.0 |
| Valpara¨ªso | 0.692363 | 0.174514 | 0.249814 | 0.405196 | 0.380127 | 0.339170 | 0.177603 | 0.047514 | -0.061269 | 0.058999 | 2.464031 | 2.0 |
| Los Lagos | 0.204969 | 0.577425 | 0.254603 | 0.254766 | 0.565572 | -0.127404 | -0.209206 | -0.038840 | -0.032185 | 0.184970 | 1.634671 | 3.0 |
| Antofagasta | -0.023722 | -0.210598 | -0.075573 | 0.003949 | -0.066772 | 0.367888 | 0.126460 | 0.436016 | 0.197444 | 0.076666 | 0.831759 | 4.0 |
| Biob¨ªo | 0.312954 | -0.259354 | 0.138733 | -0.096586 | 0.019311 | -0.044464 | 0.453489 | -0.071235 | -0.087292 | 0.079230 | 0.444784 | 5.0 |
| Tarapac¨¢ | -0.173136 | -0.013629 | -0.063857 | -0.051780 | -0.111462 | -0.139428 | 0.184253 | 0.111514 | -0.033586 | -0.196716 | -0.487826 | 6.0 |
| Coquimbo | -0.250916 | 0.091873 | -0.128560 | 0.049329 | -0.217581 | -0.327888 | -0.296003 | -0.271570 | 0.128133 | -0.040475 | -1.263659 | 7.0 |
| Magallanes y Ant¨¢rtica | -0.241153 | -0.050395 | -0.178714 | -0.167379 | -0.057579 | 0.318268 | -0.475825 | -0.242200 | -0.206185 | -0.120398 | -1.421559 | 8.0 |
| Araucan¨ªa | -0.510915 | -0.330403 | -0.159923 | 0.004307 | -0.067661 | -0.402073 | 0.026774 | -0.323501 | 0.013958 | 0.052154 | -1.697282 | 9.0 |
| Arica y Parinacota | -0.415952 | 0.084054 | -0.227440 | -0.142092 | 0.074729 | -0.219562 | -0.431607 | -0.218964 | -0.127449 | -0.193358 | -1.817640 | 10.0 |
| Atacama | -0.315089 | -0.340057 | -0.188900 | -0.203309 | -0.415831 | -0.059748 | -0.323617 | -0.149980 | 0.054979 | -0.156984 | -2.098536 | 11.0 |
| Los R¨ªos | -0.294472 | 0.045124 | -0.245964 | -0.086307 | -0.333723 | -0.381948 | -0.423620 | -0.316565 | -0.131099 | -0.070488 | -2.239061 | 12.0 |
| O'Higgins | -0.571647 | -0.122728 | -0.138538 | -0.318736 | -0.295041 | -0.319237 | -0.415101 | -0.064561 | -0.184920 | -0.053559 | -2.484068 | 13.0 |
| Maule | -0.476902 | -0.145830 | -0.227193 | -0.242213 | -0.240416 | -0.494721 | -0.279228 | -0.305912 | -0.114380 | -0.006079 | -2.532874 | 14.0 |
| Ays¨¦n | -0.441574 | -0.012318 | -0.253732 | -0.422402 | -0.465189 | -0.302594 | -0.322888 | -0.210162 | -0.088698 | -0.261150 | -2.780706 | 15.0 |

# PCA

14. Comments on regions

main strengths and opportunity areas

Metropolitana：The region perfoms comprehensively well in all 10 dimensions. Its main strengths are in dim 1 CULTURAL HERITAGE AND EVENTS and in dim 7 SECURITY AND SAFETY. The reason is that ranking scores of Metropolitana in these dimensions are over 2.2 while those of other regions are only 0.1 or below 0. The opportunity area is NATURAL RESOURCES AND SUSTAINABILITY. Low scores are in % OF LAND THAT CORRESPONDS TO FORESTS, NATIONAL PROTECTED SITES (%) and PRESERVED SITES and SEASHORE PROTECTED SITES. Need more awareness and investment in these areas to help improve the sustainability of Metropolitana.

# PCA

14. Comments on regions

Los Lagos: This region has a best score in the ranking of NATURAL RESOURCES AND SUSTAINABILITY, which is its strength. It also does well in TOURISM MOBILITY AND TRANSPORTATION INFRASTRUCTURE.The opportunity areas are in TOURISM-RELATED SERVICES, SECURITY AND SAFETY, ECONOMIC PERFORMANCE and TOURISM PROMOTION.

Valparaiso: This region performs above the average except in TOURISM PROMOTION, which is the opportunity area. Specific details are Number of tourism information offices and Yearly budget for international tourism promotion ($M). Invest on these areas will be useful.

# Recommendation

Previously, my team's recommendation is to invest more on natural sustainability and transportation infrastructure. This is in a broad view. My current recommendation is that get rid of some of the regions that contribute to tourism and focus more on some specific regions. Regions such as Aysén, Maule, O'Higgins perform poorly comprehensively. They might not be a suitable place for tourism. In terms of advertisement, the government should invest more on publicizing Metropolitana, Valparaiso, Los Lagos to attract tourists in the world. These regions should be the main focus and flagship tourism regions. Meanwhile, invest more on sustainability,  SECURITY AND SAFETY and TOURISM PROMOTION on these areas because these areas have a relatively low scores, and improving them is achievable by more budget.

To sum up, I would say invest more on sustainability on regions that have a good natural resource, which is a base advantage, such as Los Lagos, advertise more on flagship regions Metropolitana, Valparaiso and Los Lagos, build more tourism related infrastructure and transportation infrastructure on these areas to accommodate more tourists, get rid of regions such as Aysén, Maule, O'Higgins as tourism places.

# Highlights

Creating flagship regions for tourism: Metropolitana, Valparaíso, Los Lagos

Metropolitana: Can invest more in Tourism Promotion and continue improving Security and Safety

Valparaíso: Ranks low on Tourism Promotion, but has highest Governmental resources allocated to tourism promotion ($M). Low number of tourism offices

Los Lagos: Focus on Tourism-Related Services

General Plan for the country: Jan - Mar Tourism Promotion through Social Medium, Apr - June Infrastructure Improvement and Workforce Development, July - Sep  Technology Development for Potential Peak Traveling Period, Oct - Dec Monitoring, evaluating and ameliorating strategy

# Execution Plan-Post Covid 19

First 3 Months:

1. Financing
   a. Government budget (perform financial planning)
   b. Allocate resource
   c. Expected revenue; anticipated outcomes; disclosure of fees
2. Covid-19 Control

   a. Government policy

3. Infrastructure research

# Execution Plan-Post Covid 19

Month 4-10:

1. Improve Infrastructure (Los Rios, Maule, O'Higgins)

    a. Transportation (airport, highway and road, seaport)

        i. Contacties payments and options

    b. Public service (police station, hospital...)

        i. Infrastructure resilience in healthcare

2. Tourism related Services (Maule, Los Rios, Aysen)

    a. Hotels and restaurants

    b. Entertainments

    c. Outdoor events

3. HR (aysen as an example)

    a. Workforce

4. Natural sustainability (Arica y Parinacota, Biobio, Metropolitana)

    a. Tourism policy

    b. Government involvement

# Execution Plan-Post Covid 19

Month 11-12:

1. Promotion (Los Rios, O’Higgins, Magallanes y Antártica)

    a. Advertisement (internet)

    b. Deals/bonus (Flights, travel packages)

2. Result assessment & actions adjustment

# Covid Considerations

| Region | Density of restaurants per 100,000 habitants | People working at restaurants per 10,000 habitants | Car rental agencies | Hospital beds per 10,000 habitants |
|---|---|---|---|---|
| Metropolitana | 0.027651 | 0.003034 | 0.291889 | 0.001947 |
| Antofagasta | -0.003268 | -0.001249 | 0.054452 | 0.040697 |
| Valpara¨ªso | -0.019993 | -0.003931 | -0.002533 | 0.021514 |
| Magallanes y Ant¨¢rtica | -0.027274 | -0.006771 | -0.040523 | 0.081745 |
| Biob¨ªo | 0.022239 | 0.003707 | -0.002533 | 0.016326 |
| Atacama | -0.011625 | 0.000719 | 0.025960 | 0.001686 |
| Los Lagos | -0.002349 | 0.000620 | 0.073447 | -0.022981 |

1) As Covid-19 reshapes the global tourism market, it is important to develop contingencies and plans to support communities reliant on tourism during pandemic situations.
2) These areas should consider their hospital bed density including a tourist population, not merely by habitants.

   a. This is particularly important for areas with low populations but high tourist activity

3) Also important to have a balance of industries that cater to tourism with others that can persist through downtime