1. Handling Missing Data

Import Required Libraries

In [1]:
```
import pandas as pd
import numpy as np
```

Create DataFrame

In [2]:
```
missing_data_df = pd.DataFrame(
    {
        "Students": ["Tom", "Peter",np.nan, "Mary", "Tom","King","Tom","Mary",np.nan],
        "Exam_Date": ["15/01/2021", "16/01/2021", "19/01/2021", "27/01/2021", "16/01/2021",
                      "16/01/2021", "16/01/2021", "16/01/2021", "16/01/2021"],
        "Math": [79.00, 67.00,np.nan, np.nan, 70.00,np.nan,90.00,76.00,np.nan],
        "Physics":[63.00, np.nan, 60.00, np.nan,84.00, 77.00,55.00,np.nan,66.00],
        "Computer":[np.nan,78.00, 57.00, 88.00, np.nan,np.nan,np.nan,70.00,np.nan],
    }
)

missing_data_df
```

Out[2]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	NaN
1	Peter	16/01/2021	67.0	NaN	78.0
2	NaN	19/01/2021	NaN	60.0	57.0
3	Mary	27/01/2021	NaN	NaN	88.0
4	Tom	16/01/2021	70.0	84.0	NaN
5	King	16/01/2021	NaN	77.0	NaN
6	Tom	16/01/2021	90.0	55.0	NaN
7	Mary	16/01/2021	76.0	NaN	70.0
8	NaN	16/01/2021	NaN	66.0	NaN

Show null values and return false if not null

In [3]:
```
missing_data_df.isnull().head()
```

Out[3]:

	Students	Exam_Date	Math	Physics	Computer
0	False	False	False	False	True
1	False	False	False	True	False
2	True	False	True	False	False
3	False	False	True	True	False
4	False	False	False	False	True

Show count of null values

In [4]:
```
missing_data_df.isnull().sum()
```

Out[4]:
```
Students     2
Exam_Date    0
Math         4
Physics      3
Computer     5
dtype: int64
```

Show not null values and return true if not null

In [5]:
```
missing_data_df.notnull().head()
```

Out[5]:

	Students	Exam_Date	Math	Physics	Computer
0	True	True	True	True	False
1	True	True	True	False	True
2	False	True	False	True	True
3	True	True	False	False	True
4	True	True	True	True	False

1. Deleting records with missing values

Drop entire row with all values null

In [6]:
```
missing_data_df.dropna(how='all')
```

Out[6]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	NaN
1	Peter	16/01/2021	67.0	NaN	78.0
2	NaN	19/01/2021	NaN	60.0	57.0
3	Mary	27/01/2021	NaN	NaN	88.0
4	Tom	16/01/2021	70.0	84.0	NaN
5	King	16/01/2021	NaN	77.0	NaN
6	Tom	16/01/2021	90.0	55.0	NaN
7	Mary	16/01/2021	76.0	NaN	70.0
8	NaN	16/01/2021	NaN	66.0	NaN

Drop column with any null value

In [7]:
```
missing_data_df.dropna(how='any',axis=1)
```

Out[7]:

	Exam_Date
0	15/01/2021
1	16/01/2021
2	19/01/2021
3	27/01/2021
4	16/01/2021
5	16/01/2021
6	16/01/2021
7	16/01/2021
8	16/01/2021

Drop rows with any of specified columns have null

In [8]:
```
missing_data_df.dropna(subset=['Math', 'Physics'], how='any')
```

Out[8]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	NaN
4	Tom	16/01/2021	70.0	84.0	NaN
6	Tom	16/01/2021	90.0	55.0	NaN

Drop rows with all of specified columns have null

In [9]:
```
missing_data_df.dropna(subset=['Math', 'Physics'], how='all')
```

Out[9]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	NaN
1	Peter	16/01/2021	67.0	NaN	78.0
2	NaN	19/01/2021	NaN	60.0	57.0
4	Tom	16/01/2021	70.0	84.0	NaN
5	King	16/01/2021	NaN	77.0	NaN
6	Tom	16/01/2021	90.0	55.0	NaN
7	Mary	16/01/2021	76.0	NaN	70.0
8	NaN	16/01/2021	NaN	66.0	NaN

Drop row with a given number of null values

In [10]:
```
missing_data_df.dropna(axis=1,thresh=2)
```

Out[10]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	NaN
1	Peter	16/01/2021	67.0	NaN	78.0
2	NaN	19/01/2021	NaN	60.0	57.0
3	Mary	27/01/2021	NaN	NaN	88.0
4	Tom	16/01/2021	70.0	84.0	NaN
5	King	16/01/2021	NaN	77.0	NaN
6	Tom	16/01/2021	90.0	55.0	NaN
7	Mary	16/01/2021	76.0	NaN	70.0
8	NaN	16/01/2021	NaN	66.0	NaN

2. Imputation

Replace null values with a scalar value

In [11]:
```
missing_data_df.fillna(-999) # replace null values with -999
```

Out[11]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	-999.0
1	Peter	16/01/2021	67.0	-999.0	78.0
2	-999	19/01/2021	-999.0	60.0	57.0
3	Mary	27/01/2021	-999.0	-999.0	88.0
4	Tom	16/01/2021	70.0	84.0	-999.0
5	King	16/01/2021	-999.0	77.0	-999.0
6	Tom	16/01/2021	90.0	55.0	-999.0
7	Mary	16/01/2021	76.0	-999.0	70.0
8	-999	16/01/2021	-999.0	66.0	-999.0

Backward Fill

In [12]:
```
missing_data_df.fillna(method='bfill')
```

Out[12]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	78.0
1	Peter	16/01/2021	67.0	60.0	78.0
2	Mary	19/01/2021	70.0	60.0	57.0
3	Mary	27/01/2021	70.0	84.0	88.0
4	Tom	16/01/2021	70.0	84.0	70.0
5	King	16/01/2021	90.0	77.0	70.0
6	Tom	16/01/2021	90.0	55.0	70.0
7	Mary	16/01/2021	76.0	66.0	70.0
8	NaN	16/01/2021	NaN	66.0	NaN

Forward Fill

In [13]:
```
missing_data_df.fillna(method='ffill')
```

Out[13]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	NaN
1	Peter	16/01/2021	67.0	63.0	78.0
2	Peter	19/01/2021	67.0	60.0	57.0
3	Mary	27/01/2021	67.0	60.0	88.0
4	Tom	16/01/2021	70.0	84.0	88.0
5	King	16/01/2021	70.0	77.0	88.0
6	Tom	16/01/2021	90.0	55.0	88.0
7	Mary	16/01/2021	76.0	55.0	70.0
8	Mary	16/01/2021	76.0	66.0	70.0

Impute null value with statistical measures

In [14]:
```
missing_data_df.fillna(missing_data_df.Math.mean()) # fillna null value in Math column with mean of the Math
missing_data_df.fillna(missing_data_df.Students.mode()) # fillna null value in Students column with mode of the Studen
ts
missing_data_df.fillna(missing_data_df.Computer.median()) # fillna null value in Computer column with median of the Co
mputer
```

Out[14]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	74.0
1	Peter	16/01/2021	67.0	74.0	78.0
2	74	19/01/2021	74.0	60.0	57.0
3	Mary	27/01/2021	74.0	74.0	88.0
4	Tom	16/01/2021	70.0	84.0	74.0
5	King	16/01/2021	74.0	77.0	74.0
6	Tom	16/01/2021	90.0	55.0	74.0
7	Mary	16/01/2021	76.0	74.0	70.0
8	74	16/01/2021	74.0	66.0	74.0

3. Interpolate missing values

Interpolate missing data in forward direction

In [15]:
```
missing_data_df.interpolate(method='linear', limit_direction ='forward')
```

Out[15]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	NaN
1	Peter	16/01/2021	67.0	61.5	78.0
2	NaN	19/01/2021	68.0	60.0	57.0
3	Mary	27/01/2021	69.0	72.0	88.0
4	Tom	16/01/2021	70.0	84.0	83.5
5	King	16/01/2021	80.0	77.0	79.0
6	Tom	16/01/2021	90.0	55.0	74.5
7	Mary	16/01/2021	76.0	60.5	70.0
8	NaN	16/01/2021	76.0	66.0	70.0

Interpolate missing data in backward direction

In [16]:
```
missing_data_df.interpolate(method='linear', limit_direction ='backward')
```

Out[16]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	78.0
1	Peter	16/01/2021	67.0	61.5	78.0
2	NaN	19/01/2021	68.0	60.0	57.0
3	Mary	27/01/2021	69.0	72.0	88.0
4	Tom	16/01/2021	70.0	84.0	83.5
5	King	16/01/2021	80.0	77.0	79.0
6	Tom	16/01/2021	90.0	55.0	74.5
7	Mary	16/01/2021	76.0	60.5	70.0
8	NaN	16/01/2021	NaN	66.0	NaN

4. Model-based techniques

Nearest neighbors imputation

In [17]:
```
from sklearn.impute import KNNImputer
```

In [18]:
```
missing_data_df
```

Out[18]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	NaN
1	Peter	16/01/2021	67.0	NaN	78.0
2	NaN	19/01/2021	NaN	60.0	57.0
3	Mary	27/01/2021	NaN	NaN	88.0
4	Tom	16/01/2021	70.0	84.0	NaN
5	King	16/01/2021	NaN	77.0	NaN
6	Tom	16/01/2021	90.0	55.0	NaN
7	Mary	16/01/2021	76.0	NaN	70.0
8	NaN	16/01/2021	NaN	66.0	NaN

In [19]:
```
imputer = KNNImputer(n_neighbors=2, weights="uniform")
imputed_data=imputer.fit_transform(missing_data_df[['Math','Physics','Computer']].to_numpy())
imputed_data
```

Out[19]:
```
array([[79. , 63. , 63.5],
       [67. , 73.5, 78. ],
       [84.5, 60. , 57. ],
       [71.5, 61.5, 88. ],
       [70. , 84. , 74. ],
       [74.5, 77. , 67.5],
       [90. , 55. , 63.5],
       [76. , 73.5, 70. ],
       [84.5, 66. , 67.5]])
```

In [20]:
```
pd.concat([missing_data_df[['Students','Exam_Date']],pd.DataFrame(imputed_data,columns=['Math','Physics','Computer'
])],axis=1)
```

Out[20]:

	Students	Exam_Date	Math	Physics	Computer
0	Tom	15/01/2021	79.0	63.0	63.5
1	Peter	16/01/2021	67.0	73.5	78.0
2	NaN	19/01/2021	84.5	60.0	57.0
3	Mary	27/01/2021	71.5	61.5	88.0
4	Tom	16/01/2021	70.0	84.0	74.0
5	King	16/01/2021	74.5	77.0	67.5
6	Tom	16/01/2021	90.0	55.0	63.5
7	Mary	16/01/2021	76.0	73.5	70.0
8	NaN	16/01/2021	84.5	66.0	67.5

2. Handling Imbalanced Data

Load Data

In [21]:
```
import matplotlib.pyplot as plt

titanic_df=pd.read_csv('titanic.csv')
titanic_df.head()
```

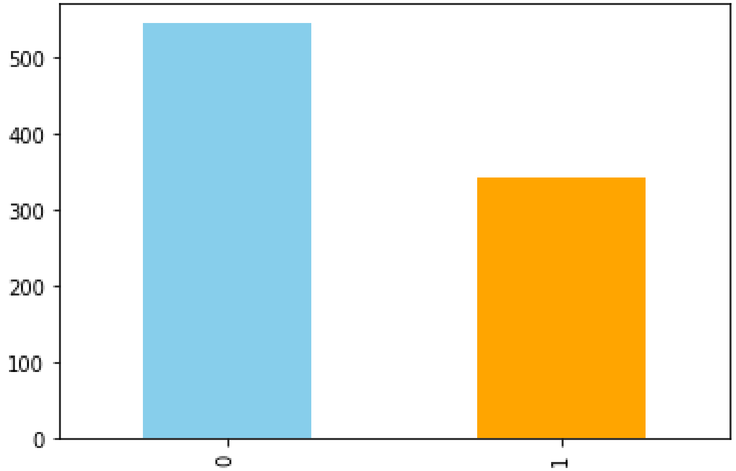
Out[21]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
0	0	3	Mr. Owen Harris Braund	male	22.0	1	0	7.2500
1	1	1	Mrs. John Bradley (Florence Briggs Thayer) Cum...	female	38.0	1	0	71.2833
2	1	3	Miss. Laina Heikkinen	female	26.0	0	0	7.9250
3	1	1	Mrs. Jacques Heath (Lily May Peel) Futrelle	female	35.0	1	0	53.1000
4	0	3	Mr. William Henry Allen	male	35.0	0	0	8.0500

Check for Class Imbalance in Data

In [22]:
```
titanic_df['Survived'].value_counts().plot(kind='bar',color=['skyblue','orange'])
```

Out[22]: <AxesSubplot:>



1. K-Fold Cross-Validation

Sklearn has KFold(n_splits=5, *, shuffle=False, random_state=None) class that splits the dataset into k consecutive folds (without shuffling by default). the n_splits sets the number of folds.

Let's fit a regression model on titanic data with KFold cross validation

In [23]:
```
# import required libraries
from sklearn.model_selection import KFold, cross_val_score
from sklearn.linear_model import LogisticRegression
#Get features and target variables from data
X=titanic_df[['Pclass','Age','Siblings/Spouses Aboard','Parents/Children Aboard','Fare']]
y=titanic_df['Survived']
# prepare cross-validation data with 10 folds
cv=KFold(n_splits=10, shuffle=True, random_state=1)
# model
model=LogisticRegression()
#Evaluate model with cv
score=cross_val_score(model,X,y,scoring='accuracy',cv=cv)
print('Min Accuracy %.2f'% (score.min()*100),'%')
print('Max Accuracy %.2f'% (score.max()*100),'%')
print('Mean Accuracy %.2f'% (np.mean(score)*100),'%')
```

```
Min Accuracy 62.92 %
Max Accuracy 77.27 %
Mean Accuracy 69.57 %
```

Let's determine the value of k (folds) with higher acuracy

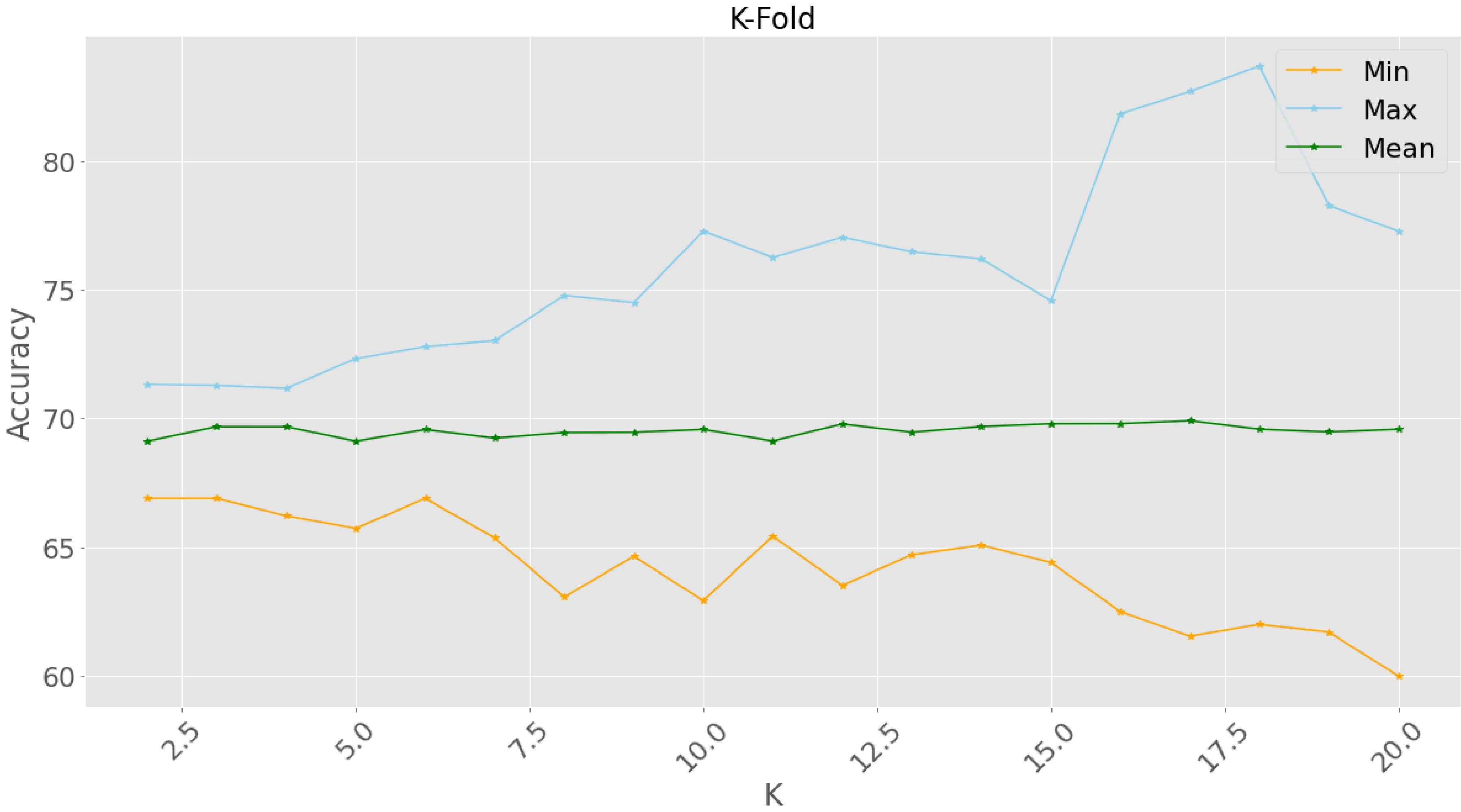
In [24]:

```
def model_evaluation(cv,X,y):
    model=LogisticRegression()
    score=cross_val_score(model,X,y,scoring='accuracy',cv=cv)
    return score.min(), score.max(),np.mean(score)

folds=range(2,21)
min_cv,max_cv,mean_cv=list(),list(),list()
#iterate through each value of fold/k
for k in folds:
    cv=KFold(n_splits=k,shuffle=True,random_state=1)
    k_min,k_max,k_mean=model_evaluation(cv,X,y)
    min_cv.append(k_min*100),max_cv.append(k_max*100),mean_cv.append(k_mean*100)
    print('Folds=%d || Min Acc. %.2f || Max Acc. %.2f || Mean Acc.%.2f' % (k,k_min,k_max,k_mean))
```

```
Folds=2 || Min Acc. 0.67 || Max Acc. 0.71 || Mean Acc.0.69
Folds=3 || Min Acc. 0.67 || Max Acc. 0.71 || Mean Acc.0.70
Folds=4 || Min Acc. 0.66 || Max Acc. 0.71 || Mean Acc.0.70
Folds=5 || Min Acc. 0.66 || Max Acc. 0.72 || Mean Acc.0.69
Folds=6 || Min Acc. 0.67 || Max Acc. 0.73 || Mean Acc.0.70
Folds=7 || Min Acc. 0.65 || Max Acc. 0.73 || Mean Acc.0.69
Folds=8 || Min Acc. 0.63 || Max Acc. 0.75 || Mean Acc.0.69
Folds=9 || Min Acc. 0.65 || Max Acc. 0.74 || Mean Acc.0.69
Folds=10 || Min Acc. 0.63 || Max Acc. 0.77 || Mean Acc.0.70
Folds=11 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.69
Folds=12 || Min Acc. 0.64 || Max Acc. 0.77 || Mean Acc.0.70
Folds=13 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.69
Folds=14 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.70
Folds=15 || Min Acc. 0.64 || Max Acc. 0.75 || Mean Acc.0.70
Folds=16 || Min Acc. 0.62 || Max Acc. 0.82 || Mean Acc.0.70
Folds=17 || Min Acc. 0.62 || Max Acc. 0.83 || Mean Acc.0.70
Folds=18 || Min Acc. 0.62 || Max Acc. 0.84 || Mean Acc.0.70
Folds=19 || Min Acc. 0.62 || Max Acc. 0.78 || Mean Acc.0.69
Folds=20 || Min Acc. 0.60 || Max Acc. 0.77 || Mean Acc.0.70
```

In [25]:

```
import matplotlib.pyplot as plt
plt.style.use('ggplot') # Other sytles to use; fivethirtyeight

plt.figure(figsize=(20,10)) # Set figure size
plt.rcParams.update({'font.size': 22}) # Set axes size
plt.plot(folds,min_cv,color='orange',marker='*') # Plot the minimum accuracy
plt.plot(folds,max_cv,color='skyblue',marker='*') # Plot the maximum accuracy
plt.plot(folds,mean_cv,color='green',marker='*') # Plot the mean accuracy
plt.title('K-Fold',fontsize=24)
plt.xticks(rotation=45)
plt.xlabel('K',fontsize=24)
plt.ylabel('Accuracy',fontsize=24)
plt.legend(['Min','Max','Mean'], loc='upper right')
plt.show()
```



2. Oversampling

i. Simple random oversampling

We will use imbalanced-learn which is a python package for data re-sampling. To install imbalanced-learn open terminal and run

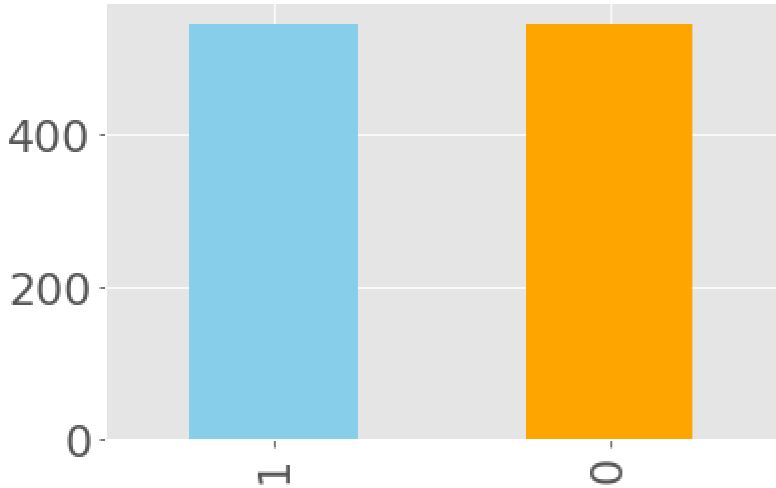
pip install imbalanced-learn

When using Anaconda run the below command on Anaconda prompt terminal

conda install -c conda-forge imbalanced-learn

In [26]:
```
from imblearn.over_sampling import RandomOverSampler

ros=RandomOverSampler()
X_resapmled,y_resampled=ros.fit_resample(X,y)
y_resampled.value_counts().plot(kind='bar',color=['skyblue','orange'])
```

Out[26]: <AxesSubplot:>

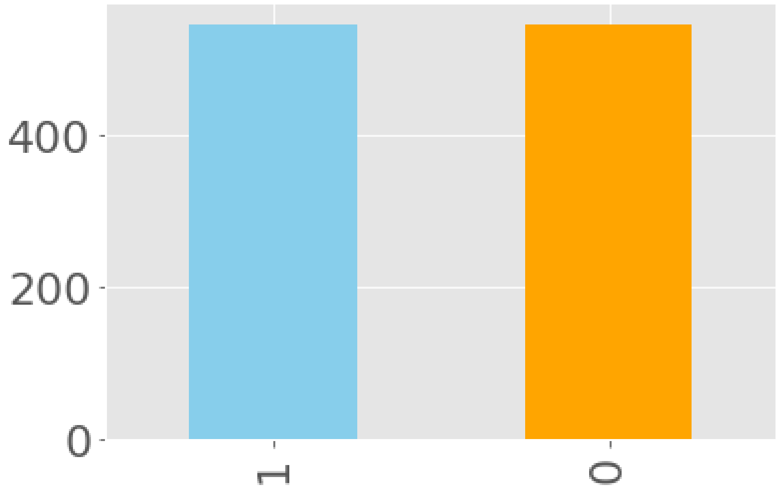


ii. Oversampling by shrinkage

We use imbalanced-learn library which comes with RandomOverSampler classs but in this case we add shrinkage parameter

In [27]:
```
from imblearn.over_sampling import RandomOverSampler

ros=RandomOverSampler(shrinkage=0.15)
X_resapmled,y_resampled=ros.fit_resample(X,y)
y_resampled.value_counts().plot(kind='bar',color=['skyblue','orange'])
```

Out[27]: <AxesSubplot:>

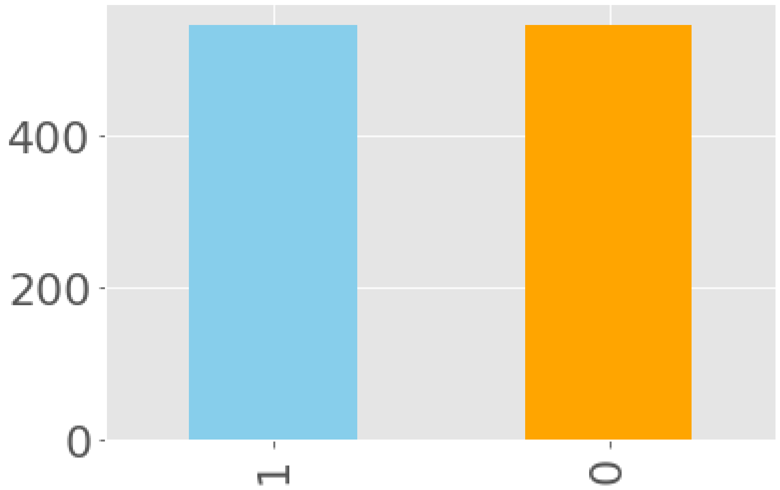


iii. Oversampling with SMOTE

The imbalanced-learn package comes with SMOTE class for synthetic sampling

In [28]:
```
from imblearn.over_sampling import SMOTE

smote=SMOTE()
X_resampled,y_resampled=smote.fit_resample(X,y)
y_resampled.value_counts().plot(kind='bar',color=['skyblue','orange'])
```

Out[28]: <AxesSubplot:>



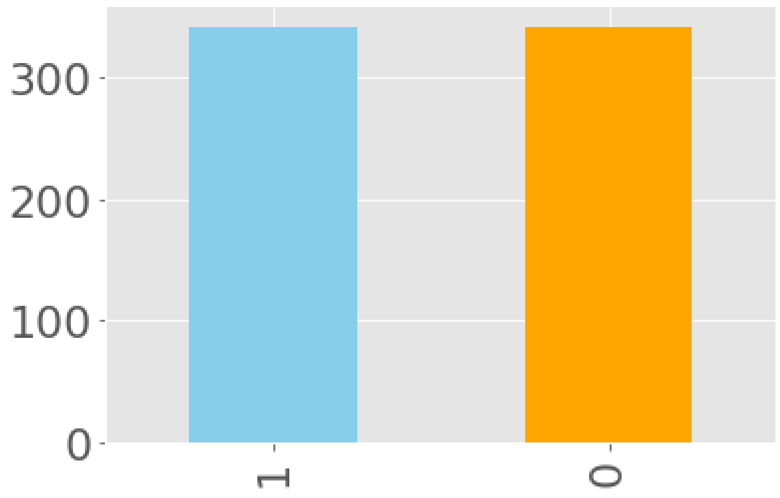
3. Undersampling

i. Simple random undersampling

We use imbalanced-learn which comes with RandomUnderSampler class for undersampling data

In [29]:
```
from imblearn.under_sampling import RandomUnderSampler

rus=RandomUnderSampler()
X_resampled,y_resampled=rus.fit_resample(X,y)
y_resampled.value_counts().plot(kind='bar',color=['skyblue','orange'])
```

Out[29]: <AxesSubplot:>

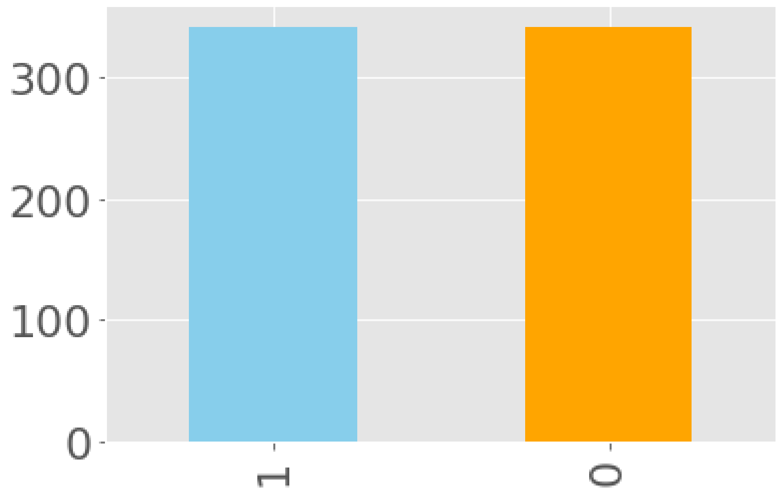


ii. Undersampling with K-Means

The imbalanced-learn library contains the ClusterCentroids class for creating clusters for undersampling

In [30]:
```
from imblearn.under_sampling import ClusterCentroids

cc=ClusterCentroids()
X_resampled,y_resampled=cc.fit_resample(X,y)
y_resampled.value_counts().plot(kind='bar',color=['skyblue','orange'])
```

Out[30]: <AxesSubplot:>



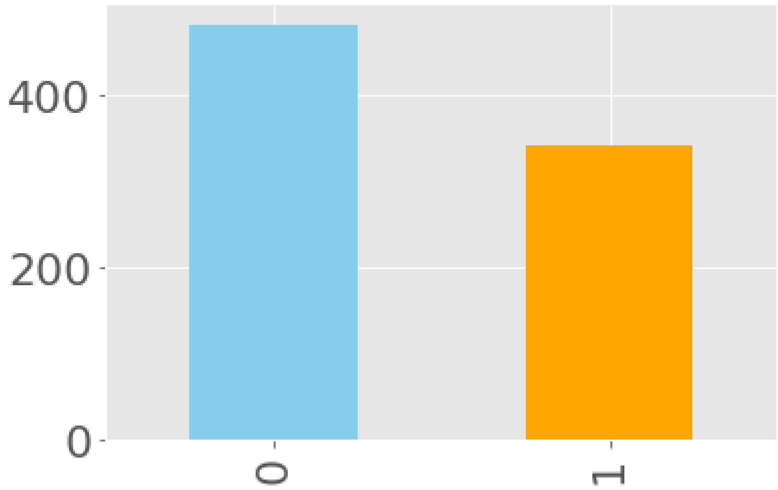
iii. Undersampling using Tomek links

The imbalanced-learn library comes with TomekLinks class which we use for undersampling.

Note that the resultant samples for each class are not the same. This is because Tomek Links only removes the samples from majority class that are close to minority class.

In [31]:
```
from imblearn.under_sampling import TomekLinks

tl=TomekLinks()
X_resampled,y_resampled=tl.fit_resample(X,y)
y_resampled.value_counts().plot(kind='bar',color=['skyblue','orange'])
```

Out[31]: <AxesSubplot:>

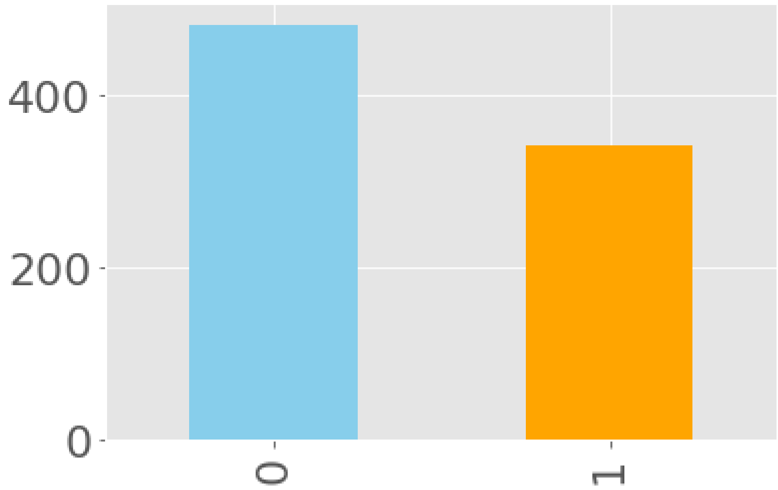


4. Oversampling and Undersampling

To get a robust way to deal with imbalanced data we can combine both oversampling and undersampling techniques. The imbalanced-learn library comes with a SMOTETomek class which is used for oversampling and undersampling.

In [32]:
```
from imblearn.combine import SMOTETomek

st=SMOTETomek()
X_resampled,y_Resampled=st.fit_resample(X,y)
y_resampled.value_counts().plot(kind='bar',color=['skyblue','orange'])
```

Out[32]: <AxesSubplot:>



3. Outliers in Data

Load data

In [33]:
```
continental_temperature_df=pd.read_csv('continental_temperature.csv')
continental_temperature_df.head()
```

Out[33]:

	Region	Year	AvgTemperature
0	Africa	1995	0.976737
1	Africa	1996	48.348380
2	Africa	1997	37.282495
3	Africa	1998	30.327075
4	Africa	1999	14.153869

1. Z-score for outlier detection

Note that we filte routliers based on Z-Score value of >2 or <2

In [34]:
```
from scipy import stats

z_score_temperature=stats.zscore(continental_temperature_df['AvgTemperature'])
continental_temperature_df['Z-Score']=z_score_temperature # create new column for z-score
continental_temperature_df[(continental_temperature_df['Z-Score']<-2) | (continental_temperature_df['Z-Score']>2)] # f
ilter samples Z-score value <-2 and >2
```

Out[34]:

	Region	Year	AvgTemperature	Z-Score
0	Africa	1995	0.976737	-2.842742
4	Africa	1999	14.153869	-2.209245
37	Asia	2006	162.959178	4.944641
44	Asia	2013	167.478655	5.161917
86	Europe	2003	13.504275	-2.240474
121	Middle East	2012	200.381547	6.743740
155	North America	2020	17.406831	-2.052857
174	South/Central America & Carribean	2013	113.894057	2.585812
178	South/Central America & Carribean	2017	129.952968	3.357852

2. Interquatile Range

i. Interquartile Range using scipy iqr

In [35]:
```
iqr=stats.iqr(continental_temperature_df['AvgTemperature'],interpolation='midpoint')
iqr
```

Out[35]: 14.318334585000002

ii. Interquartile Range using percentile function

In [36]:
```
Q1=np.percentile(continental_temperature_df['AvgTemperature'], 25, interpolation='midpoint')
Q3=np.percentile(continental_temperature_df['AvgTemperature'], 75, interpolation='midpoint')

iqr=Q3-Q1
print("Q1 : ",Q1,"\nQ3 : ",Q3,"\nIQR : ",iqr)
```

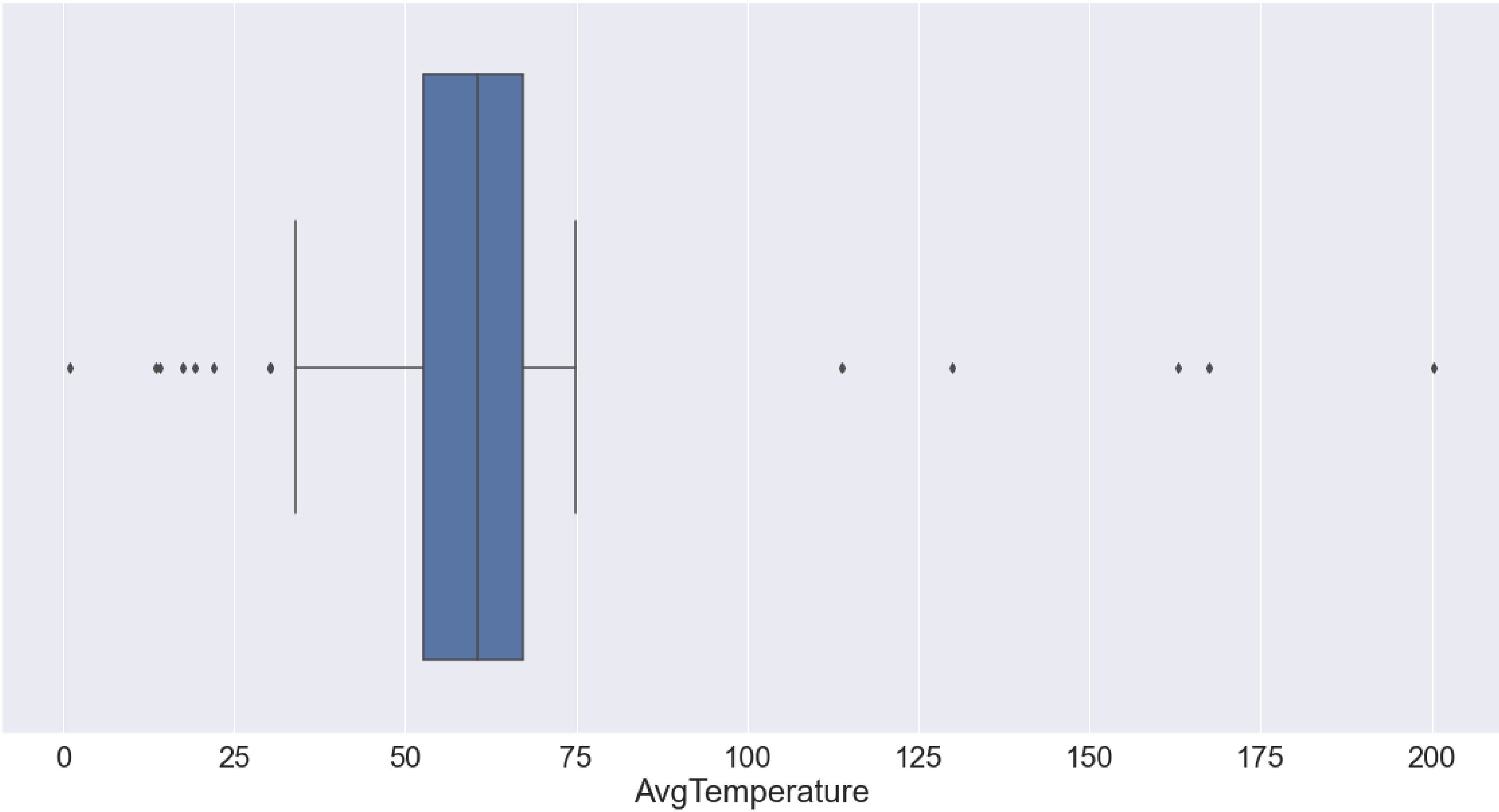
```
Q1 :  52.85268644
Q3 :  67.171021025
IQR :  14.318334585000002
```

3. Boxplot

In [37]:

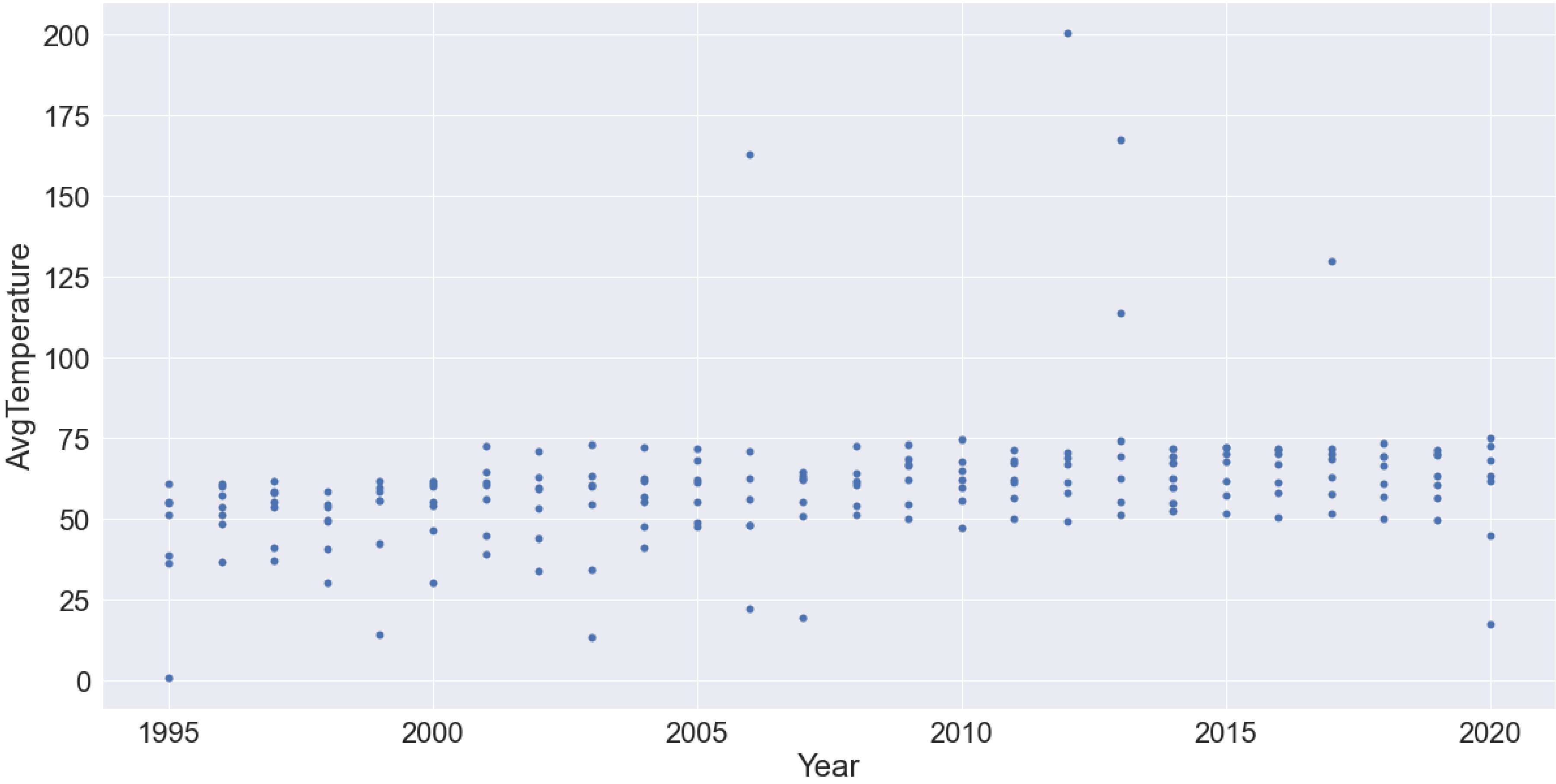
```
import matplotlib.pyplot as plt
import seaborn as sns

sns.set(rc={'figure.figsize':(20,10)}) # Set figure size

plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
plt.rcParams['text.color'] = 'blue'
plt.rcParams['font.size'] = 20

sns.boxplot(continental_temperature_df['AvgTemperature'])
plt.show()
```

```
C:\Users\soongaya\Anaconda3\lib\site-packages\seaborn\_decorators.py:43: FutureWarning: Pass the following variable a
s a keyword arg: x. From version 0.12, the only valid positional argument will be `data`, and passing other arguments
without an explicit keyword will result in an error or misinterpretation.
  FutureWarning
```



4. Scatter plot

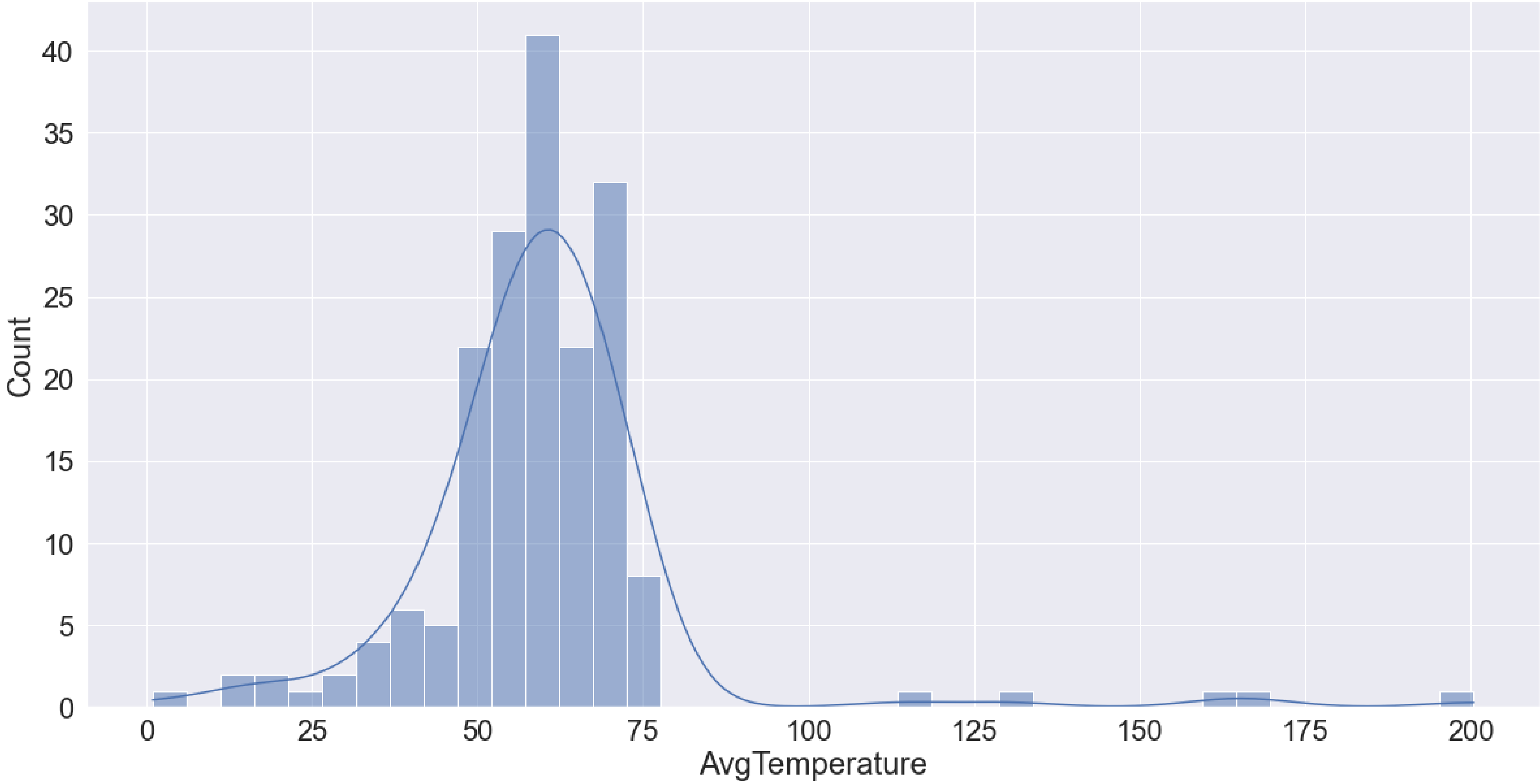
In [38]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
sns.scatterplot(x="Year", y="AvgTemperature", sizes=(1, 8), linewidth=0,data=continental_temperature_df)
plt.show()
```



5. Histogram

Histogram with Kernel Density Estimation

In [39]:
```
plt.rcParams['axes.labelsize'] = 20
sns.set(font_scale = 2)
plt.rcParams['text.color'] = 'blue'
plt.rcParams['font.size'] = 20

sns.histplot(continental_temperature_df, x='AvgTemperature',kde=True)
plt.show()
```



6. DBSCAN for Outlier Detection

The output of 1- implies that the data point is an outlier

In [40]:
```
from sklearn.cluster import DBSCAN

data=continental_temperature_df['AvgTemperature'].to_numpy().reshape(-1, 1)
dbscan=DBSCAN(min_samples=2, eps=3)
clusters=dbscan.fit_predict(data)
continental_temperature_df['dbscan_outliers']=clusters
continental_temperature_df[continental_temperature_df['dbscan_outliers']<0] # Show outlier data poins
```

Out[40]:

	Region	Year	AvgTemperature	Z-Score	dbscan_outliers
0	Africa	1995	0.976737	-2.842742	-1
37	Asia	2006	162.959178	4.944641	-1
44	Asia	2013	167.478655	5.161917	-1
121	Middle East	2012	200.381547	6.743740	-1
174	South/Central America & Carribean	2013	113.894057	2.585812	-1
178	South/Central America & Carribean	2017	129.952968	3.357852	-1

7. Isolation Forest

The sklearn.ensemble class has a function called IsolationForest that returns the anomaly score of each sample using the IsolationForest algorithm.The contamination parameter determines the he amount of contamination of the data set, i.e. the proportion of outliers in the data set. Used when fitting to define the threshold on the scores of the samples. The output of 1- implies that the data point is an outlier

In [41]:
```
from sklearn.ensemble import IsolationForest

data=continental_temperature_df['AvgTemperature'].to_numpy().reshape(-1, 1)
isf=IsolationForest()
model=isf.fit_predict(data)

continental_temperature_df['isolation_forest_outliers']=model
continental_temperature_df[continental_temperature_df['isolation_forest_outliers']==-1] # Show outlier data poins
```

Out[41]:

	Region	Year	AvgTemperature	Z-Score	dbscan_outliers	isolation_forest_outliers
0	Africa	1995	0.976737	-2.842742	-1	-1
2	Africa	1997	37.282495	-1.097325	0	-1
3	Africa	1998	30.327075	-1.431710	1	-1
4	Africa	1999	14.153869	-2.209245	2	-1
5	Africa	2000	30.256454	-1.435105	1	-1
6	Africa	2001	39.146197	-1.007727	0	-1
7	Africa	2002	34.032093	-1.253590	0	-1
8	Africa	2003	34.280538	-1.241645	0	-1
25	Africa	2020	74.867798	0.709606	0	-1
37	Asia	2006	162.959178	4.944641	-1	-1
44	Asia	2013	167.478655	5.161917	-1	-1
63	Australia/South Pacific	2006	22.066667	-1.828833	3	-1
78	Europe	1995	38.634474	-1.032328	0	-1
79	Europe	1996	36.537590	-1.133137	0	-1
82	Europe	1999	42.250435	-0.858489	0	-1
86	Europe	2003	13.504275	-2.240474	2	-1
116	Middle East	2007	19.231481	-1.965136	3	-1
119	Middle East	2010	74.841066	0.708321	0	-1
121	Middle East	2012	200.381547	6.743740	-1	-1
122	Middle East	2013	74.096354	0.672519	0	-1
155	North America	2020	17.406831	-2.052857	3	-1
156	South/Central America & Carribean	1995	36.252988	-1.146819	0	-1
174	South/Central America & Carribean	2013	113.894057	2.585812	-1	-1

	Region	Year	AvgTemperature	Z-Score	dbscan_outliers	isolation_forest_outliers
178	South/Central America & Carribean	2017	129.952968	3.357852	-1	-1

8. Local Outlier Factor

sklearn.neighbors class has a function called LocalOutlierFactor which is an outlier detection technique based on unsupervised approach. It measures the local deviation of the density of a given sample with respect to its neighbors. It is local in that the anomaly score depends on how isolated the object is with respect to the surrounding neighborhood. https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.LocalOutlierFactor.html (https://scikit-learn.org/stable/modules/generated/sklearn.neighbors.LocalOutlierFactor.html).

The fit_predict method returns -1 for outlier data point or 1 for normal data point

In [42]:

```
from sklearn.neighbors import LocalOutlierFactor

data=continental_temperature_df['AvgTemperature'].to_numpy().reshape(-1, 1)
lof=LocalOutlierFactor(n_neighbors=2)
lof_model=lof.fit_predict(data)

continental_temperature_df['lof_outliers']=lof_model
continental_temperature_df[continental_temperature_df['lof_outliers']==-1] # Show outlier data poins
```

Out[42]:

	Region	Year	AvgTemperature	Z-Score	dbscan_outliers	isolation_forest_outliers	lof_outliers
0	Africa	1995	0.976737	-2.842742	-1	-1	-1
6	Africa	2001	39.146197	-1.007727	0	-1	-1
7	Africa	2002	34.032093	-1.253590	0	-1	-1
8	Africa	2003	34.280538	-1.241645	0	-1	-1
15	Africa	2010	59.913363	-0.009335	0	1	-1
17	Africa	2012	69.160824	0.435241	0	1	-1
31	Asia	2000	54.118454	-0.287928	0	1	-1
36	Asia	2005	61.214857	0.053235	0	1	-1
38	Asia	2007	62.564065	0.118099	0	1	-1
40	Asia	2009	66.562027	0.310302	0	1	-1
45	Asia	2014	67.266177	0.344155	0	1	-1
49	Asia	2018	66.411548	0.303068	0	1	-1
57	Australia/South Pacific	2000	61.784699	0.080630	0	1	-1
59	Australia/South Pacific	2002	59.302055	-0.038724	0	1	-1
61	Australia/South Pacific	2004	61.856512	0.084083	0	1	-1
68	Australia/South Pacific	2011	62.133881	0.097417	0	1	-1
73	Australia/South Pacific	2016	61.365027	0.060454	0	1	-1
77	Australia/South Pacific	2020	68.114303	0.384929	0	1	-1
82	Europe	1999	42.250435	-0.858489	0	-1	-1
83	Europe	2000	46.421670	-0.657955	0	1	-1
90	Europe	2007	50.787129	-0.448083	0	1	-1
93	Europe	2010	47.098558	-0.625413	0	1	-1
100	Europe	2017	51.682540	-0.405036	0	1	-1

	Region	Year	AvgTemperature	Z-Score	dbscan_outliers	isolation_forest_outliers	lof_outliers
120	Middle East	2011	71.509041	0.548133	0	1	-1
130	North America	1995	54.884315	-0.251109	0	1	-1
136	North America	2001	55.915848	-0.201518	0	1	-1
137	North America	2002	53.367261	-0.324042	0	1	-1
143	North America	2008	54.032491	-0.292061	0	1	-1
149	North America	2014	55.040758	-0.243588	0	1	-1
166	South/Central America & Carribean	2005	68.041797	0.381443	0	1	-1
171	South/Central America & Carribean	2010	65.000600	0.235236	0	1	-1
173	South/Central America & Carribean	2012	70.458905	0.497647	0	1	-1
174	South/Central America & Carribean	2013	113.894057	2.585812	-1	-1	-1
179	South/Central America & Carribean	2018	69.446720	0.448985	0	1	-1
180	South/Central America & Carribean	2019	69.635753	0.458073	0	1	-1

9. Minimum Covariance Determinant

The sklearn.covariance class has a EllipticEnvelope function for outlier detection based on gaussian distributed dataset. https://scikit-learn.org/stable/modules/generated/sklearn.covariance.EllipticEnvelope.html (https://scikit-learn.org/stable/modules/generated/sklearn.covariance.EllipticEnvelope.html) .This fit_predict function returns -1 implies teh data point is an outlier while 1 is normal data point.

In [43]:

```
from sklearn.covariance import EllipticEnvelope

data=continental_temperature_df['AvgTemperature'].to_numpy().reshape(-1, 1)
ee=EllipticEnvelope()
ee_model=ee.fit_predict(data)

continental_temperature_df['ellipticenvelope_outliers']=ee_model
continental_temperature_df[continental_temperature_df['ellipticenvelope_outliers']==-1] # Show outlier data poins
```

Out[43]:

	Region	Year	AvgTemperature	Z-Score	dbscan_outliers	isolation_forest_outliers	lof_outliers	ellipticenvelope_outliers
0	Africa	1995	0.976737	-2.842742	-1	-1	-1	-1
2	Africa	1997	37.282495	-1.097325	0	-1	1	-1
3	Africa	1998	30.327075	-1.431710	1	-1	1	-1
4	Africa	1999	14.153869	-2.209245	2	-1	1	-1
5	Africa	2000	30.256454	-1.435105	1	-1	1	-1
7	Africa	2002	34.032093	-1.253590	0	-1	-1	-1
8	Africa	2003	34.280538	-1.241645	0	-1	-1	-1
37	Asia	2006	162.959178	4.944641	-1	-1	1	-1
44	Asia	2013	167.478655	5.161917	-1	-1	1	-1
63	Australia/South Pacific	2006	22.066667	-1.828833	3	-1	1	-1
78	Europe	1995	38.634474	-1.032328	0	-1	1	-1
79	Europe	1996	36.537590	-1.133137	0	-1	1	-1
86	Europe	2003	13.504275	-2.240474	2	-1	1	-1
116	Middle East	2007	19.231481	-1.965136	3	-1	1	-1
121	Middle East	2012	200.381547	6.743740	-1	-1	1	-1
155	North America	2020	17.406831	-2.052857	3	-1	1	-1
156	South/Central America & Carribean	1995	36.252988	-1.146819	0	-1	1	-1
174	South/Central America & Carribean	2013	113.894057	2.585812	-1	-1	-1	-1

	Region	Year	AvgTemperature	Z-Score	dbscan_outliers	isolation_forest_outliers	lof_outliers	ellipticenvelope_outliers
178	South/Central America & Carribean	2017	129.952968	3.357852	-1	-1	1	-1

4. Sampling Techniques

Load Data

In [44]:
```
titanic_df=pd.read_csv('titanic.csv')
titanic_df.tail()
```

Out[44]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
882	0	2	Rev. Juozas Montvila	male	27.0	0	0	13.00
883	1	1	Miss. Margaret Edith Graham	female	19.0	0	0	30.00
884	0	3	Miss. Catherine Helen Johnston	female	7.0	1	2	23.45
885	1	1	Mr. Karl Howell Behr	male	26.0	0	0	30.00
886	0	3	Mr. Patrick Dooley	male	32.0	0	0	7.75

1. Simple Random Sampling

Randomly select 10 samples from the population

In [45]:
```
titanic_df.sample(n=10, random_state=1)
```

Out[45]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
522	0	3	Mr. James Farrell	male	40.5	0	0	7.7500
314	1	2	Mrs. Sinai (Miriam Sternin) Kantor	female	24.0	1	0	26.0000
768	0	2	Mrs. (Mary) Mack	female	57.0	0	0	10.5000
320	1	2	Miss. Hilda Mary Slayter	female	30.0	0	0	12.3500
809	0	3	Miss. Ebba Iris Alfrida Andersson	female	6.0	4	2	31.2750
3	1	1	Mrs. Jacques Heath (Lily May Peel) Futrelle	female	35.0	1	0	53.1000
472	0	1	Mr. George Quincy Clifford	male	40.0	0	0	52.0000
205	0	3	Mr. Karl Alfred Backstrom	male	32.0	1	0	15.8500
289	1	1	Mrs. Dickinson H (Helen Walton) Bishop	female	19.0	1	0	91.0792
2	1	3	Miss. Laina Heikkinen	female	26.0	0	0	7.9250

2. Stratified Sampling

In [46]:
```
from sklearn.model_selection import StratifiedKFold

skf = StratifiedKFold(n_splits=3)
print("No. of stratas : ",skf.get_n_splits(titanic_df))

X=titanic_df.drop('Survived', axis=1)
y=titanic_df.Survived
for train_index, test_index in skf.split(X, y):
    X_train, X_test = X.iloc[train_index], X.iloc[test_index]
    y_train, y_test = y.iloc[train_index], y.iloc[test_index]
```

```
No. of stratas :  3
```

Statistical Resampling

Bootstrapping

In [47]:
```
from sklearn.utils import resample

bootstrap=resample(titanic_df, replace=True, n_samples=200, random_state=1)
print("Bootstrap Sample\n")
bootstrap
```

```
Bootstrap Sample
```

Out[47]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
37	0	3	Mr. Ernest Charles Cann	male	21.0	0	0	8.0500
235	0	2	Mr. Stephen Hold	male	44.0	1	0	26.0000
72	0	3	Mr. Apostolos Chronopoulos	male	26.0	1	0	14.4542
767	0	3	Mr. Niels Peder Jensen	male	48.0	0	0	7.8542
715	0	3	Mr. Malkolm Joackim Johnson	male	33.0	0	0	7.7750
...	...	...	...	...	...	...	...	...
811	0	1	Mr. Richard Fry	male	39.0	0	0	0.0000
646	1	3	Miss. Amy Zillah Elsie Stanley	female	23.0	0	0	7.5500
717	0	3	Mr. Svend Lauritz Jensen	male	17.0	1	0	7.0542
696	0	3	Mr. Adolf Mathias Nicolai Olsen Humblen	male	42.0	0	0	7.6500
536	1	1	Miss. Hedwig Margaritha Frolicher	female	22.0	0	2	49.5000

200 rows × 8 columns

In [48]:
```
print("Out of bag sample\n")
titanic_df.merge(bootstrap, how='inner', indicator=False)
```

```
Out of bag sample
```

Out[48]:

	Survived	Pclass	Name	Sex	Age	Siblings/Spouses Aboard	Parents/Children Aboard	Fare
0	0	3	Master. Gosta Leonard Palsson	male	2.0	3	1	21.0750
1	1	3	Miss. Marguerite Rut Sandstrom	female	4.0	1	1	16.7000
2	1	3	Miss. Marguerite Rut Sandstrom	female	4.0	1	1	16.7000
3	1	2	Mrs. (Mary D Kingcome) Hewlett	female	55.0	0	0	16.0000
4	1	2	Mrs. (Mary D Kingcome) Hewlett	female	55.0	0	0	16.0000
...	...	...	...	...	...	...	...	...
195	1	3	Master. Harold Theodor Johnson	male	4.0	1	1	11.1333
196	0	3	Mr. Cerin Balkic	male	26.0	0	0	7.8958
197	1	3	Miss. Adele Kiamie Najib	female	15.0	0	0	7.2250
198	1	1	Miss. Margaret Edith Graham	female	19.0	0	0	30.0000
199	1	1	Miss. Margaret Edith Graham	female	19.0	0	0	30.0000

200 rows × 8 columns

KFold Cross-Validation

Let's fit a regression model

In [49]:

```
# import required libraries
from sklearn.model_selection import KFold, cross_val_score
from sklearn.linear_model import LogisticRegression
#Get features and target variables from data
X=titanic_df[['Pclass','Age','Siblings/Spouses Aboard','Parents/Children Aboard','Fare']]
y=titanic_df['Survived']
# prepare cross-validation data with 10 folds
cv=KFold(n_splits=10, shuffle=True, random_state=1)
# model
model=LogisticRegression()
#Evaluate model with cv
score=cross_val_score(model,X,y,scoring='accuracy',cv=cv)
print('Min Accuracy %.2f'% (score.min()*100),'%')
print('Max Accuracy %.2f'% (score.max()*100),'%')
print('Mean Accuracy %.2f'% (np.mean(score)*100),'%')
```

```
Min Accuracy 62.92 %
Max Accuracy 77.27 %
Mean Accuracy 69.57 %
```

Let's determine the value of k (folds) with higher acuracy

In [50]:
```
def model_evaluation(cv,X,y):
    model=LogisticRegression()
    score=cross_val_score(model,X,y,scoring='accuracy',cv=cv)
    return score.min(), score.max(),np.mean(score)

folds=range(2,21)
min_cv,max_cv,mean_cv=list(),list(),list()
#iterate through each value of fold/k
for k in folds:
    cv=KFold(n_splits=k,shuffle=True,random_state=1)
    k_min,k_max,k_mean=model_evaluation(cv,X,y)
    min_cv.append(k_min*100),max_cv.append(k_max*100),mean_cv.append(k_mean*100)
    print('Folds=%d || Min Acc. %.2f || Max Acc. %.2f || Mean Acc.%.2f' % (k,k_min,k_max,k_mean))
def model_evaluation(cv,X,y):
    model=LogisticRegression()
    score=cross_val_score(model,X,y,scoring='accuracy',cv=cv)
    return score.min(), score.max(),np.mean(score)

folds=range(2,21)
min_cv,max_cv,mean_cv=list(),list(),list()
#iterate through each value of fold/k
for k in folds:
    cv=KFold(n_splits=k,shuffle=True,random_state=1)
    k_min,k_max,k_mean=model_evaluation(cv,X,y)
    min_cv.append(k_min*100),max_cv.append(k_max*100),mean_cv.append(k_mean*100)
    print('Folds=%d || Min Acc. %.2f || Max Acc. %.2f || Mean Acc.%.2f' % (k,k_min,k_max,k_mean))
```

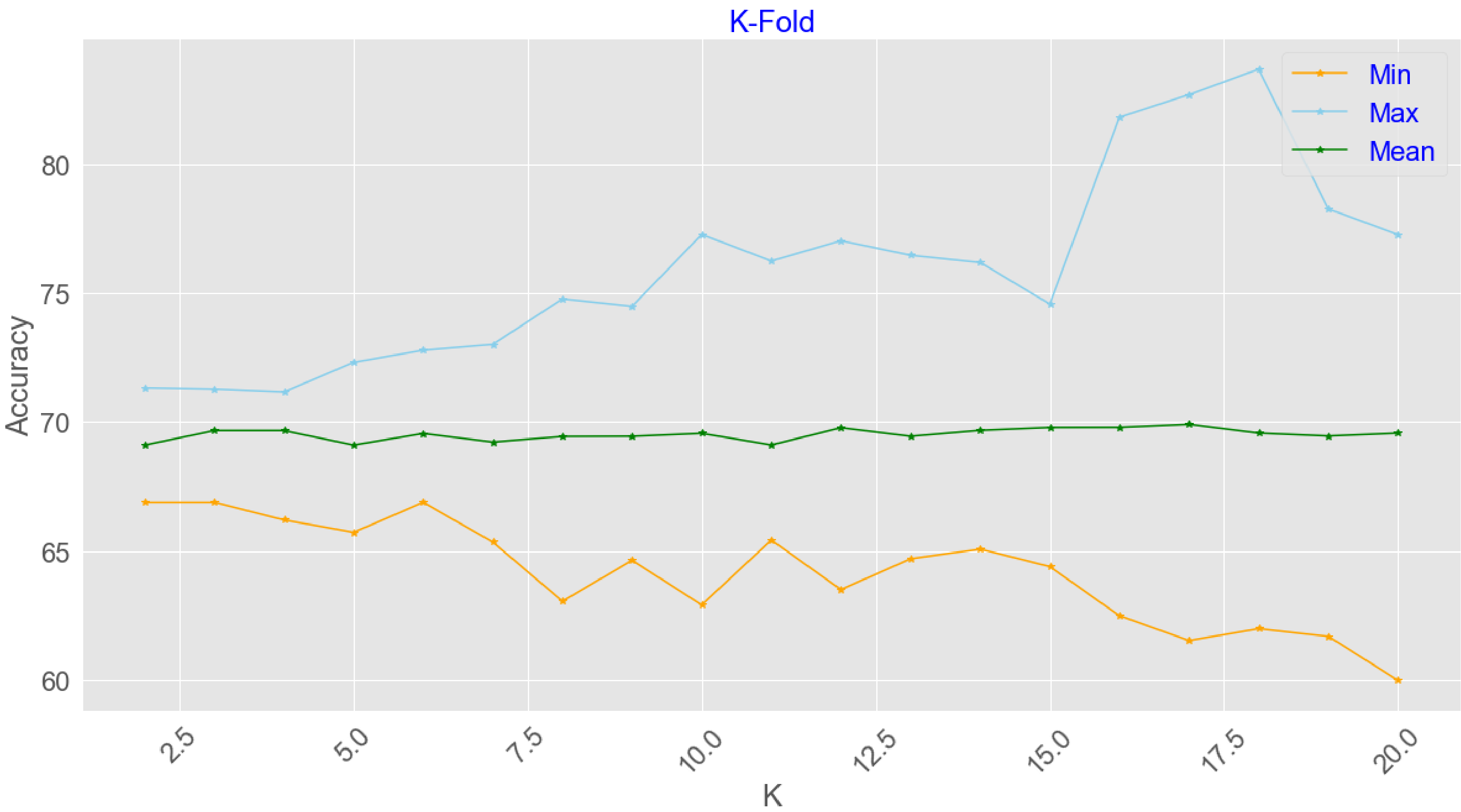
```
Folds=2 || Min Acc. 0.67 || Max Acc. 0.71 || Mean Acc.0.69
Folds=3 || Min Acc. 0.67 || Max Acc. 0.71 || Mean Acc.0.70
Folds=4 || Min Acc. 0.66 || Max Acc. 0.71 || Mean Acc.0.70
Folds=5 || Min Acc. 0.66 || Max Acc. 0.72 || Mean Acc.0.69
Folds=6 || Min Acc. 0.67 || Max Acc. 0.73 || Mean Acc.0.70
Folds=7 || Min Acc. 0.65 || Max Acc. 0.73 || Mean Acc.0.69
Folds=8 || Min Acc. 0.63 || Max Acc. 0.75 || Mean Acc.0.69
Folds=9 || Min Acc. 0.65 || Max Acc. 0.74 || Mean Acc.0.69
Folds=10 || Min Acc. 0.63 || Max Acc. 0.77 || Mean Acc.0.70
Folds=11 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.69
Folds=12 || Min Acc. 0.64 || Max Acc. 0.77 || Mean Acc.0.70
Folds=13 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.69
Folds=14 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.70
Folds=15 || Min Acc. 0.64 || Max Acc. 0.75 || Mean Acc.0.70
Folds=16 || Min Acc. 0.62 || Max Acc. 0.82 || Mean Acc.0.70
Folds=17 || Min Acc. 0.62 || Max Acc. 0.83 || Mean Acc.0.70
Folds=18 || Min Acc. 0.62 || Max Acc. 0.84 || Mean Acc.0.70
Folds=19 || Min Acc. 0.62 || Max Acc. 0.78 || Mean Acc.0.69
Folds=20 || Min Acc. 0.60 || Max Acc. 0.77 || Mean Acc.0.70
```

```
Folds=2 || Min Acc. 0.67 || Max Acc. 0.71 || Mean Acc.0.69
Folds=3 || Min Acc. 0.67 || Max Acc. 0.71 || Mean Acc.0.70
Folds=4 || Min Acc. 0.66 || Max Acc. 0.71 || Mean Acc.0.70
Folds=5 || Min Acc. 0.66 || Max Acc. 0.72 || Mean Acc.0.69
Folds=6 || Min Acc. 0.67 || Max Acc. 0.73 || Mean Acc.0.70
Folds=7 || Min Acc. 0.65 || Max Acc. 0.73 || Mean Acc.0.69
Folds=8 || Min Acc. 0.63 || Max Acc. 0.75 || Mean Acc.0.69
Folds=9 || Min Acc. 0.65 || Max Acc. 0.74 || Mean Acc.0.69
Folds=10 || Min Acc. 0.63 || Max Acc. 0.77 || Mean Acc.0.70
Folds=11 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.69
Folds=12 || Min Acc. 0.64 || Max Acc. 0.77 || Mean Acc.0.70
Folds=13 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.69
Folds=14 || Min Acc. 0.65 || Max Acc. 0.76 || Mean Acc.0.70
Folds=15 || Min Acc. 0.64 || Max Acc. 0.75 || Mean Acc.0.70
Folds=16 || Min Acc. 0.62 || Max Acc. 0.82 || Mean Acc.0.70
Folds=17 || Min Acc. 0.62 || Max Acc. 0.83 || Mean Acc.0.70
Folds=18 || Min Acc. 0.62 || Max Acc. 0.84 || Mean Acc.0.70
Folds=19 || Min Acc. 0.62 || Max Acc. 0.78 || Mean Acc.0.69
Folds=20 || Min Acc. 0.60 || Max Acc. 0.77 || Mean Acc.0.70
```

Let's plot the accuracies for the values of k

In [51]:

```
import matplotlib.pyplot as plt
plt.style.use('ggplot') # Other sytles to use; fivethirtyeight

plt.figure(figsize=(20,10)) # Set figure size
plt.rcParams.update({'font.size': 22}) # Set axes size
plt.plot(folds,min_cv,color='orange',marker='*') # Plot the minimum accuracy
plt.plot(folds,max_cv,color='skyblue',marker='*') # Plot the maximum accuracy
plt.plot(folds,mean_cv,color='green',marker='*') # Plot the mean accuracy
plt.title('K-Fold',fontsize=24)
plt.xticks(rotation=45)
plt.xlabel('K',fontsize=24)
plt.ylabel('Accuracy',fontsize=24)
plt.legend(['Min','Max','Mean'], loc='upper right')
plt.show()
```


K-Fold
Min
Max
Mean
Accuracy
80
75
70
65
60
2.5
5.0
7.5
10.0
12.5
15.0
17.5
20.0
K