In [1]:

```python
import pandas as pd
import seaborn as sns
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline

import warnings
warnings.filterwarnings('ignore')
```

Read data from processed csv file

In [2]:

```python
data = pd.read_csv('data.csv')
```

display original data

In [3]:

```python
data
```

Out[3]:

	AnimalID	ID	Breed	Color	Gender	Name	Intake-DateTime	Intake-Type	Intake-Condition	Intake-Age(days)	...	IsAdopted	Category	Inte
0	A006100	A006100	Spinone Italiano	Yellow	Male	Scamp	2014-03-07 14:26:00	Public Assist	Normal	2190	...	False	Sporting	
1	A006100	A006100+	Spinone Italiano	Yellow	Male	Scamp	2014-12-19 10:21:00	Public Assist	Normal	2555	...	False	Sporting	
2	A006100	A006100++	Spinone Italiano	Yellow	Male	Scamp	2017-12-07 14:07:00	Stray	Normal	3650	...	False	Sporting	
3	A134067	A134067	Shetland Sheepdog	Brown	Male	Bandit	2013-11-16 09:02:00	Public Assist	Injured	12190	...	False	Herding	
4	A141142	A141142	Labrador Retriever	Black	Female	Bettie	2013-11-16 14:46:00	Stray	Aged	11825	...	False	Sporting	
...	...	...	...	...	...	...	...	...	...	...	...	...	...	
85791	A893431	A893431	Chihuahua	Tricolor	Female	Chili	2023-11-21 11:21:00	Public Assist	Normal	2920	...	False	Toy	
85792	A893432	A893432	Chihuahua	Tan	Female	Coco	2023-11-21 11:21:00	Public Assist	Normal	2920	...	False	Toy	
85793	A893452	A893452	Maltese	White	Female	Sophie	2023-11-21 13:38:00	Public Assist	Normal	2555	...	False	Toy	
85794	A893529	A893529	Labrador Retriever	White	Female	Unknown	2023-11-22 14:26:00	Owner Surrender	Normal	30	...	False	Sporting	
85795	A893585	A893585	German Shepherd	Black	Male	Unknown	2023-11-23 20:19:00	Stray	Injured	30	...	False	Herding	

85796 rows × 26 columns

assign the IsAdopted colunm to y

In [4]:

```python
y = data.iloc[:,16:17]
```

In [5]:

```python
y
```

Out[5]:

	IsAdopted
0	False
1	False
2	False
3	False
4	False
...	...
85791	False
85792	False
85793	False
85794	False
85795	False

85796 rows × 1 columns

drop irrelevant data

In [6]:
```
X = data.iloc[:,:].drop(columns=["IsAdopted", "AnimalID", "ID", "Intake-DateTime","Color", "Breed","Outcome-Dat
```

In [7]:
```
X
```

Out[7]:

	Gender	Age	Intelligence-Ranking	Size-Category	Longevity	Total-Cost($)	Purchase-Cost($)	Food-Cost($)
0	Male	Adult	27	Large	9.00	18062	1725	5679
1	Male	Senior	27	Large	9.00	18062	1725	5679
2	Male	Senior	27	Large	9.00	18062	1725	5679
3	Male	Senior	6	Small	12.53	17469	465	3698
4	Female	Senior	7	Medium	12.04	18422	810	4819
...	...	...	...	...	...	...	...	...
85791	Female	Senior	67	Small	16.50	22640	588	4594
85792	Female	Senior	67	Small	16.50	22640	588	4594
85793	Female	Senior	59	Small	12.25	16073	650	2410
85794	Female	Baby	7	Medium	12.04	18422	810	4819
85795	Male	Baby	3	Large	9.73	15091	820	3895

85796 rows × 8 columns

convert literal data into numerical data

In [8]:
```
gender = X.groupby('Gender').size()
```

In [9]:
```
gender
```

Out[9]:
```
Gender
Female    39792
Male      46004
dtype: int64
```

In [10]:
```
X['Gender'].replace(['Female','Male'], [0,1], inplace=True)
```

In [11]:
```
SizeCategory = X.groupby('Size-Category').size()
```

In [12]:
```
SizeCategory
```

Out[12]:
```
Size-Category
Large     16531
Medium    44483
Small     24782
dtype: int64
```

In [13]:
```
X['Size-Category'].replace(['Large','Medium','Small'], [3,2,1], inplace=True)
```

In [14]:
```
Age = X.groupby('Age').size()
```

In [15]:
```
Age
```

Out[15]:
```
Age
Adult     33272
Baby      18294
Senior     9581
Young     24649
dtype: int64
```

In [16]:
```
X['Age'].replace(['Baby','Young','Adult', 'Senior'], [1,2,3,4], inplace=True)
```

display final X set

In [17]:
```
X
```

Out[17]:

	Gender	Age	Intelligence-Ranking	Size-Category	Longevity	Total-Cost($)	Purchase-Cost($)	Food-Cost($)
0	1	3	27	3	9.00	18062	1725	5679
1	1	4	27	3	9.00	18062	1725	5679
2	1	4	27	3	9.00	18062	1725	5679
3	1	4	6	1	12.53	17469	465	3698
4	0	4	7	2	12.04	18422	810	4819
...	...	...	...	...	...	...	...	...
85791	0	4	67	1	16.50	22640	588	4594
85792	0	4	67	1	16.50	22640	588	4594
85793	0	4	59	1	12.25	16073	650	2410
85794	0	1	7	2	12.04	18422	810	4819
85795	1	1	3	3	9.73	15091	820	3895

85796 rows × 8 columns

Step 1 Split the dataset into training and test sets (80, 20).

In [18]:
```
from sklearn.model_selection import train_test_split
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
```

Step 2(a) Use all the features to fit the linear regression model for feature (IsAdopted) using the training set.

In [19]:
```
from sklearn.linear_model import LinearRegression
regr=LinearRegression()
regr.fit(X_train,y_train)
y_pred=regr.predict(X_test)
```

Step 2(b) Report the coefficients, mean squared error and variance score for the model on the test set.

In [20]:
```
# The coefficients
print('Coefficients: ', regr.coef_)
# The mean squared error
print("Mean squared error: %.2f" % np.mean((y_pred - y_test)**2))
# Explained variance score : 1 is perfect prediction
print('Variance score: %.2f' % regr.score(X_test , y_test))
```

```
Coefficients:  [[-2.98008358e-02 -1.09621316e-01 -4.25757756e-04  5.33990460e-02
  -9.02232419e-03  1.98188870e-05 -4.94359992e-05 -2.26540735e-05]]
Mean squared error: 0.24
Variance score: 0.05
```

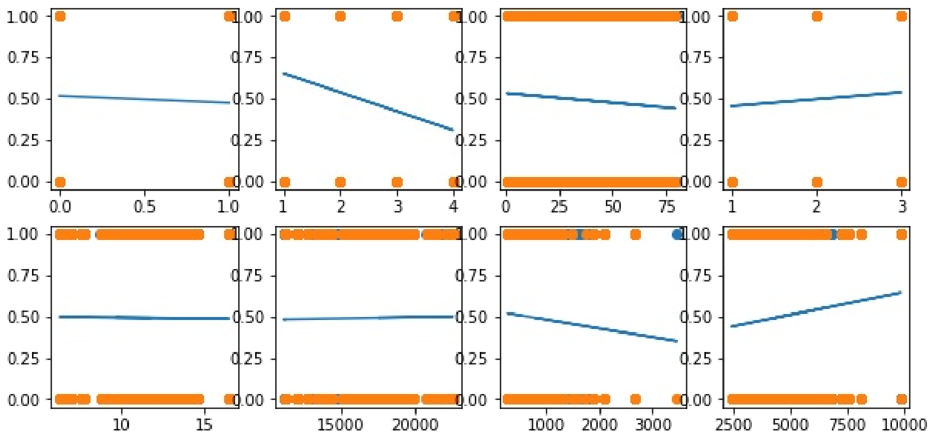
Step 3(a) Use each feature alone - to fit a linear regression model on the training set.

Step 3(b) Report the coefficient, mean squared error and variance score for the model on the test set. Also report the plots of the linear regression models generated on each feature. Each plot should distinctly show the training points, test points and the linear regression line.

In [21]:
```
plt.figure(figsize=(10,10))
names=["Gender", "Age", "Intelligence-Ranking", "Size-Category", "Longevity", "Total-Cost($)", "Purchase-Cost($
for i in range(8):
    plt.subplot(4, 4, i + 1)
    x=pd.DataFrame(X.iloc[:,i])
    x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
    regr = LinearRegression()
    regr.fit(x_train, y_train)
    y_pre =regr.predict(x_test)
    plt.scatter(x_train, y_train, label='train')
    plt.scatter(x_test, y_test, label='test')
    plt.plot(x_test.values.reshape(-1,1) , y_pre,label='line')
    print('for fit on feature: '+names[i])
    # The coefficients
    print('Coefficients: ', regr.coef_)
    # The mean squared error
    print("Mean squared error: %.2f" % (np.sum((y_pre-y_test)**2)/len(y_test)))
    # Explained variance score : 1 is perfect prediction
```

```
    print('Variance score: %.2f' % regr.score(x_test,y_test))
    print('\n')
plt.show()
```

```
for fit on feature: Gender
Coefficients:  [[-0.0420605]]
Mean squared error: 0.25
Variance score: 0.00


for fit on feature: Age
Coefficients:  [[-0.11457121]]
Mean squared error: 0.24
Variance score: 0.05


for fit on feature: Intelligence-Ranking
Coefficients:  [[-0.00116715]]
Mean squared error: 0.25
Variance score: 0.00


for fit on feature: Size-Category
Coefficients:  [[0.04183498]]
Mean squared error: 0.25
Variance score: 0.00


for fit on feature: Longevity
Coefficients:  [[-0.00090539]]
Mean squared error: 0.25
Variance score: -0.00


for fit on feature: Total-Cost($)
Coefficients:  [[1.51300583e-06]]
Mean squared error: 0.25
Variance score: 0.00


for fit on feature: Purchase-Cost($)
Coefficients:  [[-5.30642617e-05]]
Mean squared error: 0.25
Variance score: 0.00


for fit on feature: Food-Cost($)
Coefficients:  [[2.77278519e-05]]
Mean squared error: 0.25
Variance score: 0.00
```



Step 4(a) Perform 10 iterations of (Step 1, Step 2(a), and Step 3(a)).

Step 4(b) • During each iteration of Step4(a), gather the metrics - mean squared error and variance score for the models on the test set • For each feature, compute the average, over the 10 iterations, of each evaluation metric. Do the same for the metrics corresponding to 'all features'.

In [22]:
```
coef_temp=[]
mse_all=[]
vs_all=[]
coef_feas = []
mse_feas = []
vs_feas = []
for j in range(10):
    x_train, x_test, y_train, y_test = train_test_split(X, y, test_size=0.2)
    regr=LinearRegression()
    regr.fit(x_train,y_train)
    y_predict=regr.predict(x_test)
```

```python
    # The coefficients
    coef_temp.append(regr.coef_)
    # The mean squared error
    mse_all.append((np.sum((y_predict-y_test)**2)/len(y_test)))
    # Explained variance score : 1 is perfect prediction
    vs_all.append(regr.score(x_test,y_test))
for m in range(10):
    temp1 = []
    temp2 = []
    temp3 = []
    for i in range(8):
        x=pd.DataFrame(X.iloc[:,i])
        x_train, x_test, y_train, y_test = train_test_split(x, y, test_size=0.2)
        regr = LinearRegression()
        regr.fit(x_train, y_train)
        y_pre =regr.predict(x_test)
        # The coefficients
        temp1.append(regr.coef_)
        # The mean squared error
        temp2.append((np.sum((y_pre-y_test)**2)/len(y_test)))
        # Explained variance score : 1 is perfect prediction
        temp3.append(regr.score(x_test,y_test))
    coef_feas.append(temp1)
    mse_feas.append(temp2)
    vs_feas.append(temp3)
```

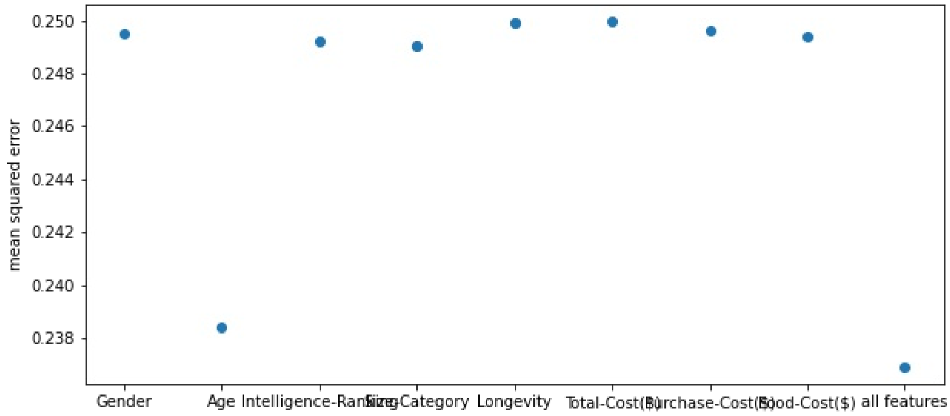
In [23]:

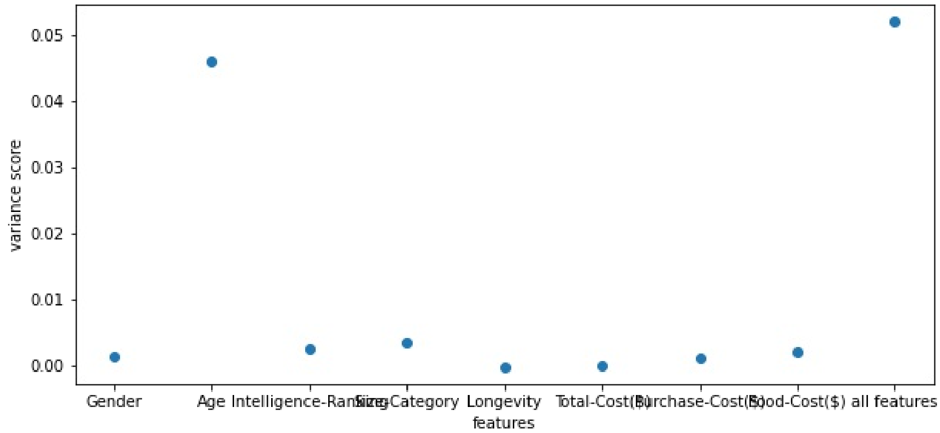
```python
coef_all=[]
coef=[]
mse=[]
vs=[]
for n in range(8):
    temp_all=0
    temp=0
    temp_mse=0
    temp_vs=0
    for a in range(10):
        temp_all+=coef_temp[a][0][n]
        temp += coef_feas[a][n]
        temp_mse+=mse_feas[a][n]
        temp_vs+=vs_feas[a][n]
    temp_all=temp_all/10
    temp=temp/10
    temp_mse=temp_mse/10
    temp_vs=temp_vs/10
    coef_all.append(temp_all)
    coef.append(temp)
    mse.append(temp_mse)
    vs.append(temp_vs)
    print('for feature: ' + names[n])
    print("Averange of coefficients: %.2f" % temp[0])
    print("Averange of mean squared error: %.2f" % mse[n])
    print("Averange of variance score: %.2f" % vs[n])
    print('\n')
print("for all features:")
print("Averange of coefficients:",coef_all)
print("Averange of mean squared error:%.2f" % (sum(mse_all) / len(mse_all)))
print("Averange of variance score:%.2f" % (sum(vs_all) / len(vs_all)))
print('\n')
```

```
for feature: Gender
Averange of coefficients: -0.04
Averange of mean squared error: 0.25
Averange of variance score: 0.00


for feature: Age
Averange of coefficients: -0.12
Averange of mean squared error: 0.24
Averange of variance score: 0.05


for feature: Intelligence-Ranking
Averange of coefficients: -0.00
Averange of mean squared error: 0.25
Averange of variance score: 0.00


for feature: Size-Category
Averange of coefficients: 0.04
Averange of mean squared error: 0.25
Averange of variance score: 0.00


for feature: Longevity
Averange of coefficients: -0.00
Averange of mean squared error: 0.25
Averange of variance score: -0.00


for feature: Total-Cost($)
Averange of coefficients: 0.00
Averange of mean squared error: 0.25
Averange of variance score: -0.00


for feature: Purchase-Cost($)
Averange of coefficients: -0.00
Averange of mean squared error: 0.25
Averange of variance score: 0.00


for feature: Food-Cost($)
Averange of coefficients: 0.00
Averange of mean squared error: 0.25
Averange of variance score: 0.00


for all features:
Averange of coefficients: [-0.027942672641134758, -0.10895360424592877, -0.00037742942189543805, 0.054820922728
85739, -0.010461782631660966, 2.0380540098449696e-05, -5.472378478391694e-05, -2.3831031868984735e-05]
Averange of mean squared error:0.24
Averange of variance score:0.05
```

In [24]:

```
plt.figure(figsize=(10, 10))
names = names + ["all features"]
mse.append((sum(mse_all) / len(mse_all)))
vs.append((sum(vs_all) / len(vs_all)))
plt.subplot(2,1,1)
s1=plt.scatter(names,mse)
plt.ylabel('mean squared error')
plt.subplot(2,1,2)
s2=plt.scatter(names,vs)
plt.ylabel('variance score')
plt.xlabel('features')
plt.show()
```





Conclusion & Discussion

From the linear regression model, we can see:

1. Gender, Longevity, Total-Cost do not affect if the pet will be adopted. The line is quite flat.

2. Intelligence-Ranking, Size-Category, Purchase-Cost have tiny effects on adoption. Intelligence-Ranking and Purchase-Cost have negative effects, meaning if a pet is less-intelligent and costs more, it has less chance to be adopted. Size-Category has the opposite positive effect.

3. Age and Food-Cost have a dramatic influence on adoption. If a pet is younger and costs less on food, it has a much bigger chance to be adopted.

4. Age is the most predictive for the target feature. It has a low average of mean squared error and high average of variance score.

5. The model performs much better with all features rather than any individual ones. This quite makes sense since the model is better trained. Some features fit the model quite well though some others do not have a quite relatively linear relationship.