In [1]:

```
import os
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
%matplotlib inline
import statsmodels.api as sm
```

In [2]:

```
pd.set_option('display.max_columns', None)
pd.set_option('display.max_rows', None)
```

In [3]:

```
df = pd.read_csv('/Users/hamadwaheed/Desktop/churn_clean.csv')
df_copy1 = df
df_copy2 = df_copy1
df_copy3 = df_copy2
df_copy4 = df_copy3
df_copy5 = df_copy4
df_copy6 = df_copy5
df_copy7 = df_copy6
```

In [ ]:

```
```

In [4]:

```
df.head()
```

Out[4]:

	CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat
0	1	K409198	aa90260b-4141-4a24-8e36-b04ce1f4f77b	e885b299883d4f9fb18e39c75155d990	Point Baker	AK	Prince of Wales-Hyder	99927	56.25100
1	2	S120509	fb76459f-c047-4a9d-8af9-e0f7d4ac2524	f2de8bef964785f41a2959829830fb8a	West Branch	MI	Ogemaw	48661	44.32893
2	3	K191035	344d114c-3736-4be5-98f7-c72c281e2d35	f1784cfa9f6d92ae816197eb175d3c71	Yamhill	OR	Yamhill	97148	45.35589
3	4	D90850	abfa2b40-2d43-4994-b15a-989b8c79e311	dc8a365077241bb5cd5ccd305136b05e	Del Mar	CA	San Diego	92014	32.96687
4	5	K662701	68a861fd-0d20-4e51-a587-8a90407ee574	aabb64a116e83fdc4befc1fbab1663f9	Needville	TX	Fort Bend	77461	29.38012

Part I: Research Question

A. Describe the purpose of this data analysis by doing the following:

A. Describe the purpose of this data analysis by doing the following:

1. A common pattern in modern day internet and phone companies is high Customer churn. Which means the turnover rate. Consumers move to compaies with better packages and more reliable services. In this highly competitive industry, we want to increase tenure rate and decrese churn rate. The reason we are talking about Churn is because our reserach question emanates from the idea of churn. We want to know what variables contribute most to tenure, becuase a longer tenure equates to a smaller churn rate. Our research question is, just like how light, water, and clean air in different combinations contribute to plant growth, what combination of variables within this dataset contribute to a longer tenure?
2. The objectives or goals of this project:

   - estimate an increased life expectancy of costumer's contract with the company: i.e predict whether a certain combination of variables can increase the length of tenure, becuase this will in turn decrease churn.

Part II: Method Justification

1. Mulitple linear regression is a machine learning algorithm capable of outputting predictor values from input variables. It works by using explanatory or input variables, which can be continious or categorical, to determine a relationship to the output value. It used in predicting continous variable (Tenure in our case). The key assumptions of Muliptle Linear Regression are:

   - A linear relationship between indicator and output variables
   - No correlation between input variables
   - Variance when it comes to residuals
   - Multivariate Normality
2. Our analysis is carried out using python because of its;

   - Faster Development and Processing
   - Powerful Packages
   - Better Data Visualisation
3. Multiple linear regession is an appropriate technique to use because we can see the effect of multiple x variables and how they impact the dependent Y variable. We also want to see the strength of the relationship between the variables. A company can take into consideration whether there is a strong relationship between variables when predicting what type of packages or products to offer. There will be stronger relationships with certain variables, and we want to find out which ones those are.

To prepare the data we will start by checking if it is clean and if it has any null points. We will also encode catergorical variables as dummy variables an standardize them to use them in the model. we will also normalize our data and use labelencoder for our pre-processing. we will do this to create an OLS model after our regression model. From there we will utilize the output p-values as selection criteria for reduction.

In [5]:

```
print('Dimensionality of the data is {}'.format(df.shape))   # .shape returns a tupel
print('The data set has {} cases.'.format(df.shape[0]))      # we can also index the elemen
ts of that tupel
print('The total number of elements is {}.'.format(df.size))
df_copy1.info()
```

```
Dimensionality of the data is (10000, 50)
The data set has 10000 cases.
The total number of elements is 500000.
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 columns):
 #   Column                 Non-Null Count  Dtype
---  ------                 --------------  -----
 0   CaseOrder              10000 non-null  int64
 1   Customer_id            10000 non-null  object
 2   Interaction            10000 non-null  object
 3   UID                    10000 non-null  object
 4   City                   10000 non-null  object
 5   State                  10000 non-null  object
```

```
 6   County                10000 non-null  object
 7   Zip                   10000 non-null  int64
 8   Lat                   10000 non-null  float64
 9   Lng                   10000 non-null  float64
 10  Population            10000 non-null  int64
 11  Area                  10000 non-null  object
 12  TimeZone              10000 non-null  object
 13  Job                   10000 non-null  object
 14  Children              10000 non-null  int64
 15  Age                   10000 non-null  int64
 16  Income                10000 non-null  float64
 17  Marital               10000 non-null  object
 18  Gender                10000 non-null  object
 19  Churn                 10000 non-null  object
 20  Outage_sec_perweek    10000 non-null  float64
 21  Email                 10000 non-null  int64
 22  Contacts              10000 non-null  int64
 23  Yearly_equip_failure  10000 non-null  int64
 24  Techie                10000 non-null  object
 25  Contract              10000 non-null  object
 26  Port_modem            10000 non-null  object
 27  Tablet                10000 non-null  object
 28  InternetService       10000 non-null  object
 29  Phone                 10000 non-null  object
 30  Multiple              10000 non-null  object
 31  OnlineSecurity        10000 non-null  object
 32  OnlineBackup          10000 non-null  object
 33  DeviceProtection      10000 non-null  object
 34  TechSupport           10000 non-null  object
 35  StreamingTV           10000 non-null  object
 36  StreamingMovies       10000 non-null  object
 37  PaperlessBilling      10000 non-null  object
 38  PaymentMethod         10000 non-null  object
 39  Tenure                10000 non-null  float64
 40  MonthlyCharge         10000 non-null  float64
 41  Bandwidth_GB_Year     10000 non-null  float64
 42  Item1                 10000 non-null  int64
 43  Item2                 10000 non-null  int64
 44  Item3                 10000 non-null  int64
 45  Item4                 10000 non-null  int64
 46  Item5                 10000 non-null  int64
 47  Item6                 10000 non-null  int64
 48  Item7                 10000 non-null  int64
 49  Item8                 10000 non-null  int64
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

In [6]:

```
df_copy1.describe()
```

Out[6]:

	CaseOrder	Zip	Lat	Lng	Population	Children	Age	Income	Outag
count	10000.00000	10000.000000	10000.000000	10000.000000	10000.000000	10000.0000	10000.000000	10000.000000	
mean	5000.50000	49153.319600	38.757567	-90.782536	9756.562400	2.0877	53.078400	39806.926771	
std	2886.89568	27532.196108	5.437389	15.156142	14432.698671	2.1472	20.698882	28199.916702	
min	1.00000	601.000000	17.966120	-171.688150	0.000000	0.0000	18.000000	348.670000	
25%	2500.75000	26292.500000	35.341828	-97.082813	738.000000	0.0000	35.000000	19224.717500	
50%	5000.50000	48869.500000	39.395800	-87.918800	2910.500000	1.0000	53.000000	33170.605000	
75%	7500.25000	71866.500000	42.106908	-80.088745	13168.000000	3.0000	71.000000	53246.170000	
max	10000.00000	99929.000000	70.640660	-65.667850	111850.000000	10.0000	89.000000	258900.700000	

In [7]:

```
df_copy1_null =df.isnull().sum(); pr=df.isnull().sum()/df_copy1.shape[0]
Nan=pd.concat([df_copy1_null,round(pr, 2)], axis=1, keys=["Total of missing values" ,"pourcentage (%)"]) ; Nan
```

Out[7]:

	Total of missing values	pourcentage (%)
CaseOrder	0	0.0
Customer_id	0	0.0
Interaction	0	0.0
UID	0	0.0
City	0	0.0
State	0	0.0
County	0	0.0
Zip	0	0.0
Lat	0	0.0
Lng	0	0.0
Population	0	0.0
Area	0	0.0
TimeZone	0	0.0
Job	0	0.0
Children	0	0.0
Age	0	0.0
Income	0	0.0
Marital	0	0.0
Gender	0	0.0
Churn	0	0.0
Outage_sec_perweek	0	0.0
Email	0	0.0
Contacts	0	0.0
Yearly_equip_failure	0	0.0
Techie	0	0.0
Contract	0	0.0
Port_modem	0	0.0
Tablet	0	0.0
InternetService	0	0.0
Phone	0	0.0
Multiple	0	0.0
OnlineSecurity	0	0.0
OnlineBackup	0	0.0
DeviceProtection	0	0.0
TechSupport	0	0.0
StreamingTV	0	0.0
StreamingMovies	0	0.0
PaperlessBilling	0	0.0
PaymentMethod	0	0.0
Tenure	0	0.0

	Total of missing values	pourcentage (%)
MonthlyCharge	0	0.0
Bandwidth_GB_Year	0	0.0
Item1	0	0.0
Item2	0	0.0
Item3	0	0.0
Item4	0	0.0
Item5	0	0.0
Item6	0	0.0
Item7	0	0.0
Item8	0	0.0

The data is clean and does not have any missing rows or values, we can proceed with our univariate and bivariate trends

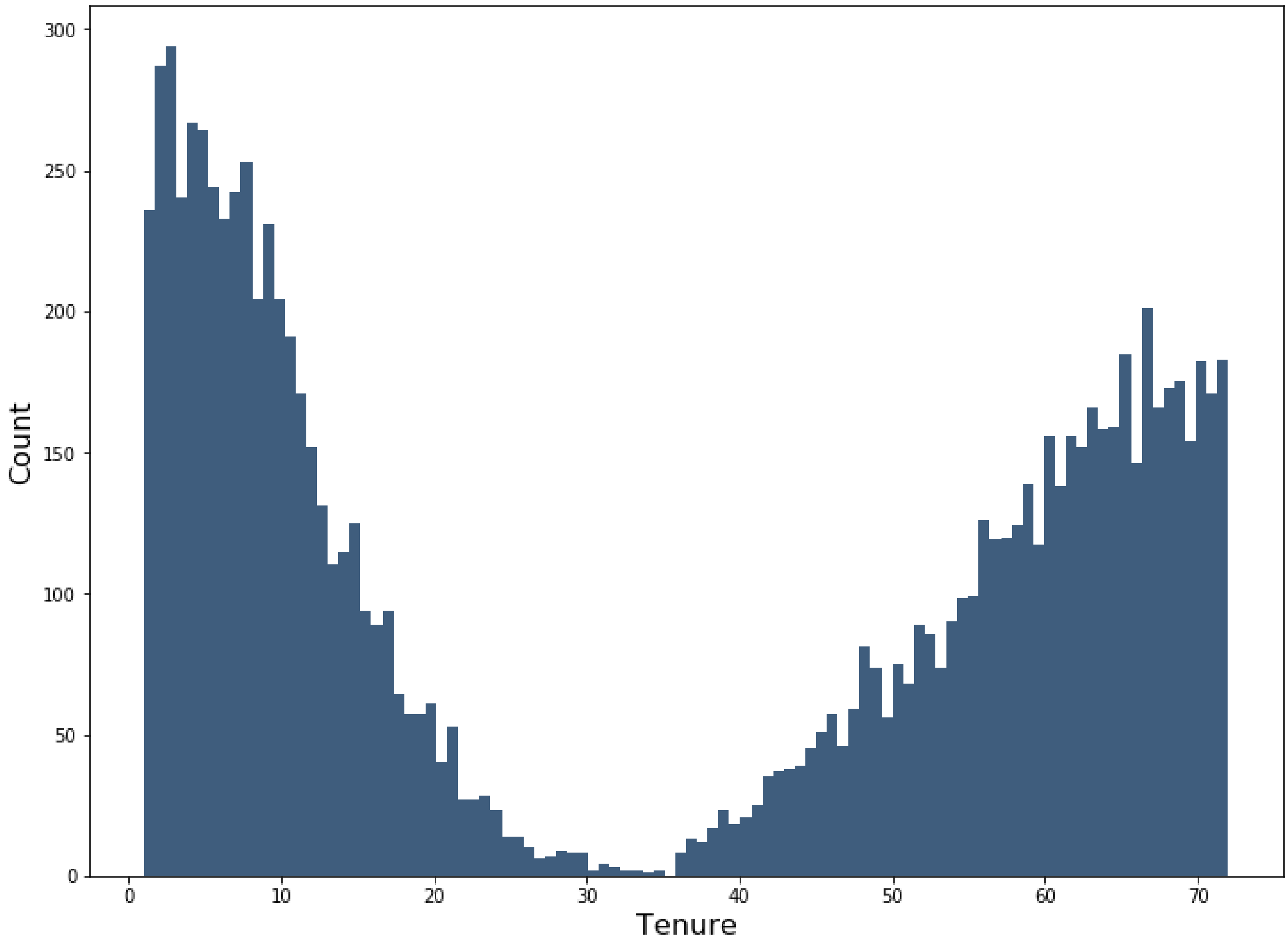
The Target Variable

In [8]:

```
plt.figure(figsize=(12, 9))
plt.xlabel("Tenure", fontsize=16)
plt.ylabel("Count", fontsize=16)
p=plt.hist(df_copy1.Tenure.values ,  color="#3F5D7D", bins=100, )
p.index
```

Out[8]:

```
<function tuple.index(value, start=0, stop=9223372036854775807, /)>
```



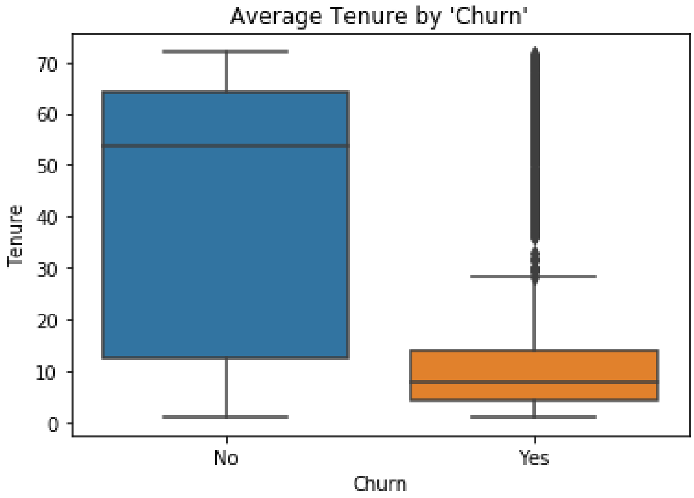
In [9]:

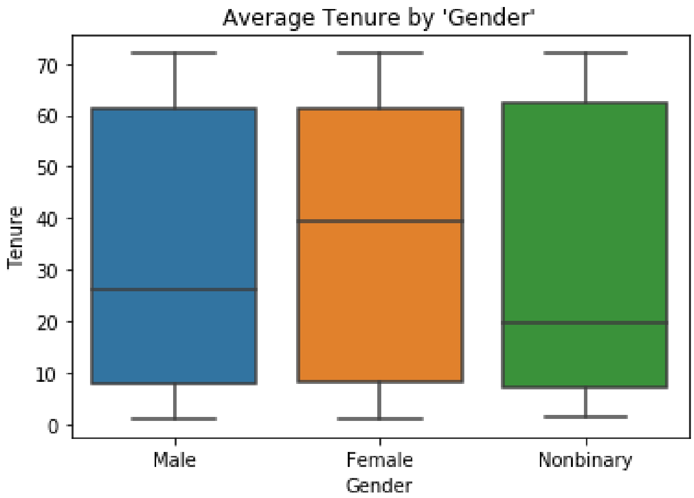
```
ax=sns.boxplot(x='Churn',y='Tenure',data=df_copy1)
```

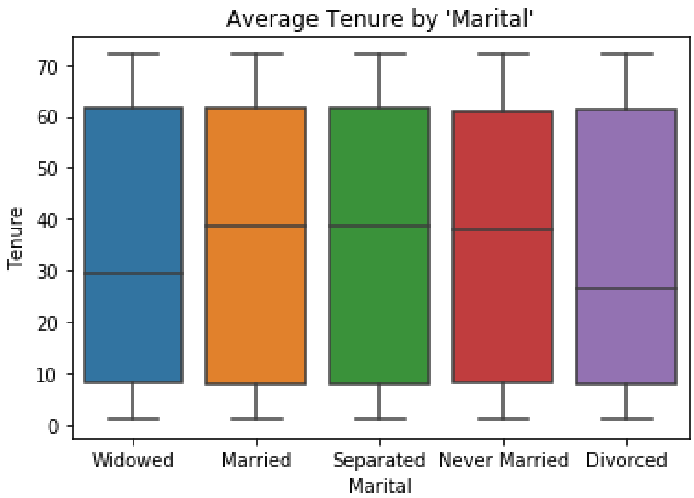
```
ax.set_title("Average Tenure by 'Churn'")
ax.set_ylabel('Tenure')
plt.show()

ax=sns.boxplot(x='Gender',y='Tenure',data=df_copy1)
ax.set_title("Average Tenure by 'Gender'")
ax.set_ylabel('Tenure')
plt.show()


ax=sns.boxplot(x='Marital',y='Tenure',data=df_copy1)
ax.set_title("Average Tenure by 'Marital'")
ax.set_ylabel('Tenure')
plt.show()
```





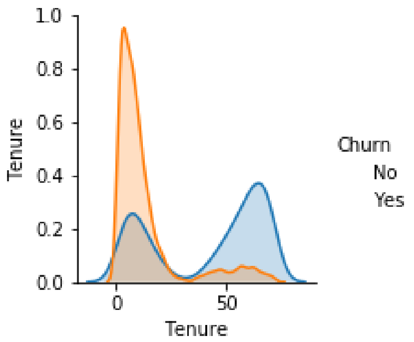


In [10]:

```
f=df_copy1[['Tenure','Churn']]
f.head()
sns.pairplot(f, hue='Churn')
```

Out[10]:

```
<seaborn.axisgrid.PairGrid at 0x7fb5ff954c10>
```



In [ ]:

In [ ]:

In [ ]:

Visualization Preperation End

In [ ]:

In [11]:

```
df_copy1.head()
```

Out[11]:

	CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat
0	1	K409198	aa90260b-4141-4a24-8e36-b04ce1f4f77b	e885b299883d4f9fb18e39c75155d990	Point Baker	AK	Prince of Wales-Hyder	99927	56.25100
1	2	S120509	fb76459f-c047-4a9d-8af9-e0f7d4ac2524	f2de8bef964785f41a2959829830fb8a	West Branch	MI	Ogemaw	48661	44.32893
2	3	K191035	344d114c-3736-4be5-98f7-c72c281e2d35	f1784cfa9f6d92ae816197eb175d3c71	Yamhill	OR	Yamhill	97148	45.35589
3	4	D90850	abfa2b40-2d43-4994-b15a-989b8c79e311	dc8a365077241bb5cd5ccd305136b05e	Del Mar	CA	San Diego	92014	32.96687
4	5	K662701	68a861fd-0d20-4e51-a587-8a90407ee574	aabb64a116e83fdc4befc1fbab1663f9	Needville	TX	Fort Bend	77461	29.38012

In [12]:

```
df_copy1.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 50 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   CaseOrder             10000 non-null  int64  
 1   Customer_id           10000 non-null  object 
 2   Interaction           10000 non-null  object 
 3   UID                   10000 non-null  object 
 4   City                  10000 non-null  object 
 5   State                 10000 non-null  object 
 6   County                10000 non-null  object 
 7   Zip                   10000 non-null  int64  
 8   Lat                   10000 non-null  float64
 9   Lng                   10000 non-null  float64
 10  Population            10000 non-null  int64  
 11  Area                  10000 non-null  object 
 12  TimeZone              10000 non-null  object 
 13  Job                   10000 non-null  object 
 14  Children              10000 non-null  int64  
 15  Age                   10000 non-null  int64  
 16  Income                10000 non-null  float64
 17  Marital               10000 non-null  object 
 18  Gender                10000 non-null  object 
 19  Churn                 10000 non-null  object 
 20  Outage_sec_perweek    10000 non-null  float64
 21  Email                 10000 non-null  int64  
 22  Contacts              10000 non-null  int64  
 23  Yearly_equip_failure  10000 non-null  int64  
 24  Techie                10000 non-null  object 
 25  Contract              10000 non-null  object 
 26  Port_modem            10000 non-null  object 
 27  Tablet                10000 non-null  object 
 28  InternetService       10000 non-null  object 
 29  Phone                 10000 non-null  object 
 30  Multiple              10000 non-null  object 
 31  OnlineSecurity        10000 non-null  object 
 32  OnlineBackup          10000 non-null  object 
 33  DeviceProtection      10000 non-null  object 
 34  TechSupport           10000 non-null  object 
 35  StreamingTV           10000 non-null  object 
 36  StreamingMovies       10000 non-null  object 
 37  PaperlessBilling      10000 non-null  object 
 38  PaymentMethod         10000 non-null  object 
 39  Tenure                10000 non-null  float64
 40  MonthlyCharge         10000 non-null  float64
 41  Bandwidth_GB_Year     10000 non-null  float64
 42  Item1                 10000 non-null  int64  
 43  Item2                 10000 non-null  int64  
 44  Item3                 10000 non-null  int64  
 45  Item4                 10000 non-null  int64  
 46  Item5                 10000 non-null  int64  
 47  Item6                 10000 non-null  int64  
 48  Item7                 10000 non-null  int64  
 49  Item8                 10000 non-null  int64  
dtypes: float64(7), int64(16), object(27)
memory usage: 3.8+ MB
```

Initial Model

In [13]:

```
#### Pre-Processing: Creating Dummy Variables
```

We will exlude city, county, state, and timezone because the dummy variables are 400 pages long and it will dilute our data

In [14]:

```
df_copy2 = pd.get_dummies(df, columns=['StreamingTV','StreamingMovies','Gender','PaymentMethod','InternetService','Contract','Area','Techie','Port_modem','Tablet','Phone','Multiple','OnlineSecurity','OnlineBackup','DeviceProtection','TechSupport','PaperlessBilling','Marital'],drop_first=True).head(5)
```

In [15]:

```
from sklearn.linear_model import LinearRegression
from sklearn.linear_model import Lasso
from sklearn.linear_model import Ridge
from sklearn.model_selection import train_test_split #to create validation data set
from sklearn import metrics

X=df_copy2.drop(["Tenure","Interaction","Customer_id","UID","Churn","County","Job","State","City","TimeZone"], axis=1)
Y=df_copy2["Tenure"]

X.fillna(0, inplace=True)
Y.fillna(0, inplace=True)

X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.3, random_state=4)
lm = LinearRegression()
lm.fit(X_train,y_train)
predictions = lm.predict(X_test)

def regression_results(y_true, y_pred):

    # Regression metrics
    explained_variance=metrics.explained_variance_score(y_true, y_pred)
    mean_absolute_error=metrics.mean_absolute_error(y_true, y_pred)
    mse=metrics.mean_squared_error(y_true, y_pred)
   # mean_squared_log_error=metrics.mean_squared_log_error(y_true, y_pred)
    median_absolute_error=metrics.median_absolute_error(y_true, y_pred)
    r2=metrics.r2_score(y_true, y_pred)

    print('explained_variance: ', round(explained_variance,4))
    #print('mean_squared_log_error: ', round(mean_squared_log_error,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))

regression_results(y_test, predictions)
```

```
explained_variance:  -0.004
r2:  -0.0411
MAE:  5.156
MSE:  27.5681
RMSE:  5.2505
```

In [16]:

```
X = sm.add_constant(X) # adding a constant
```

In [17]:

```
model = sm.OLS(Y, X).fit()
predictions = model.predict(X)
```

In [18]:

```
print_model = model.summary()
print(print_model)
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Tenure   R-squared:                       1.000
Model:                            OLS   Adj. R-squared:                    nan
Method:                 Least Squares   F-statistic:                       nan
Date:                Mon, 30 Aug 2021   Prob (F-statistic):                nan
Time:                        00:08:21   Log-Likelihood:                 152.20
No. Observations:                   5   AIC:                            -294.4
```

```
Df Residuals:                       0   BIC:                        -296.4
Df Model:                           4
Covariance Type:            nonrobust
==========================================================================================
===============
                                          coef    std err          t      P>|t|      [
0.025      0.975]
------------------------------------------------------------------------------------------
-----------------
const                               -6.746e-05        inf         -0        nan
nan         nan
CaseOrder                              -0.0001        inf         -0        nan
nan         nan
Zip                                  9.261e-05        inf          0        nan
nan         nan
Lat                                    -0.0035        inf         -0        nan
nan         nan
Lng                                     0.0023        inf          0        nan
nan         nan
Population                           8.331e-05        inf          0        nan
nan         nan
Children                               -0.0006        inf         -0        nan
nan         nan
Age                                    -0.0001        inf         -0        nan
nan         nan
Income                              -9.014e-05        inf         -0        nan
nan         nan
Outage_sec_perweek                     -0.0003        inf         -0        nan
nan         nan
Email                                  -0.0001        inf         -0        nan
nan         nan
Contacts                                0.0003        inf          0        nan
nan         nan
Yearly_equip_failure                   -0.0002        inf         -0        nan
nan         nan
MonthlyCharge                          -0.0273        inf         -0        nan
nan         nan
Bandwidth_GB_Year                       0.0059        inf          0        nan
nan         nan
Item1                               -4.578e-05        inf         -0        nan
nan         nan
Item2                                  -0.0002        inf         -0        nan
nan         nan
Item3                                   0.0003        inf          0        nan
nan         nan
Item4                                  -0.0005        inf         -0        nan
nan         nan
Item5                               -9.795e-05        inf         -0        nan
nan         nan
Item6                                2.547e-05        inf          0        nan
nan         nan
Item7                                  -0.0004        inf         -0        nan
nan         nan
Item8                                  -0.0003        inf         -0        nan
nan         nan
StreamingTV_Yes                      3.794e-06        inf          0        nan
nan         nan
StreamingMovies_Yes                    -0.0002        inf         -0        nan
nan         nan
Gender_Male                             0.0002        inf          0        nan
nan         nan
Gender_Nonbinary                             0        nan        nan        nan
nan         nan
PaymentMethod_Credit Card (automatic) -7.126e-05      inf         -0        nan
nan         nan
PaymentMethod_Electronic Check               0        nan        nan        nan
nan         nan
PaymentMethod_Mailed Check              0.0001        inf          0        nan
nan         nan
InternetService_Fiber Optic         -7.871e-05        inf         -0        nan
nan         nan
InternetService_None                         0        nan        nan        nan
nan         nan
```

```
Contract_One year                         8.939e-05        inf          0         nan
nan          nan
Contract_Two Year                         1.125e-05        inf          0         nan
nan          nan
Area_Suburban                                0.0001        inf          0         nan
nan          nan
Area_Urban                                  -0.0002        inf         -0         nan
nan          nan
Techie_Yes                                  -0.0001        inf         -0         nan
nan          nan
Port_modem_Yes                              -0.0001        inf         -0         nan
nan          nan
Tablet_Yes                               -4.528e-05        inf         -0         nan
nan          nan
Phone_Yes                                -3.403e-05        inf         -0         nan
nan          nan
Multiple_Yes                                -0.0003        inf         -0         nan
nan          nan
OnlineSecurity_Yes                           0.0001        inf          0         nan
nan          nan
OnlineBackup_Yes                          8.939e-05        inf          0         nan
nan          nan
DeviceProtection_Yes                              0        nan        nan         nan
nan          nan
TechSupport_Yes                          -3.343e-05        inf         -0         nan
nan          nan
PaperlessBilling_Yes                     -3.403e-05        inf         -0         nan
nan          nan
Marital_Married                           3.723e-05        inf          0         nan
nan          nan
Marital_Never Married                             0        nan        nan         nan
nan          nan
Marital_Separated                        -3.343e-05        inf         -0         nan
nan          nan
Marital_Widowed                          -7.126e-05        inf         -0         nan
nan          nan
==============================================================================
Omnibus:                          nan   Durbin-Watson:                   0.832
Prob(Omnibus):                    nan   Jarque-Bera (JB):                1.757
Skew:                          -1.449   Prob(JB):                        0.415
Kurtosis:                       3.178   Cond. No.                     2.11e+03
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified
.
[2] The input rank is higher than the number of observations.
[3] The condition number is large, 2.11e+03. This might indicate that there are
strong multicollinearity or other numerical problems.
```

```
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/stats/stattools.py:71: ValueWarning
: omni_normtest is not valid with less than 8 observations; 5 samples were given.
  "samples were given." % int(n), ValueWarning)
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/regression/linear_model.py:1698: Ru
ntimeWarning: divide by zero encountered in true_divide
  return 1 - (np.divide(self.nobs - self.k_constant, self.df_resid)
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/regression/linear_model.py:1699: Ru
ntimeWarning: invalid value encountered in double_scalars
  * (1 - self.rsquared))
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/regression/linear_model.py:1620: Ru
ntimeWarning: divide by zero encountered in double_scalars
  return np.dot(wresid, wresid) / self.df_resid
/opt/anaconda3/lib/python3.7/site-packages/statsmodels/base/model.py:1446: RuntimeWarning:
invalid value encountered in multiply
  cov_p = self.normalized_cov_params * scale
/opt/anaconda3/lib/python3.7/site-packages/scipy/stats/_distn_infrastructure.py:903: Runti
meWarning: invalid value encountered in greater
  return (a < x) & (x < b)
/opt/anaconda3/lib/python3.7/site-packages/scipy/stats/_distn_infrastructure.py:903: Runti
meWarning: invalid value encountered in less
  return (a < x) & (x < b)
/opt/anaconda3/lib/python3.7/site-packages/scipy/stats/_distn_infrastructure.py:1912: Runt
```

```
ImeWarning: invalid value encountered in less_equal
  cond2 = cond0 & (x <= _a)
```

In [19]:

```
print(lm.coef_, lm.intercept_)
```

```
[ 1.95313606e-04  2.12835675e-04  9.69350624e-08 -2.29230024e-07
 -9.13278229e-05  4.60358031e-08 -1.12593636e-07 -3.00544496e-04
  1.40600665e-08 -5.53792930e-08 -1.72449904e-08  0.00000000e+00
 -4.07651611e-07  2.34636907e-05  2.75498127e-09  0.00000000e+00
 -2.01739974e-08  1.53384513e-08  0.00000000e+00 -4.49389727e-09
 -1.53384513e-08 -2.01739974e-08 -1.32725517e-08  7.24629588e-09
 -8.62249518e-09  0.00000000e+00  1.18947517e-08  0.00000000e+00
 -8.62249518e-09 -1.32725517e-08  0.00000000e+00  0.00000000e+00
  1.18947517e-08 -8.62249518e-09  7.24629588e-09  7.24629588e-09
  4.30440600e-09 -5.68140564e-09  7.24629588e-09  7.24629588e-09
 -5.68140564e-09  0.00000000e+00  0.00000000e+00 -8.62249518e-09
  7.24629588e-09 -5.68140564e-09  0.00000000e+00 -8.62249518e-09
  1.18947517e-08] -1.7419618437752042
```

In [20]:

```
print("Intercept: ", lm.intercept_)
print("Coefficients:")
list(zip(X, lm.coef_))
```

```
Intercept:  -1.7419618437752042
Coefficients:
```

Out[20]:

```
[('const', 0.00019531360578751959),
 ('CaseOrder', 0.00021283567463616296),
 ('Zip', 9.69350624186941e-08),
 ('Lat', -2.2923002378480747e-07),
 ('Lng', -9.132782287327869e-05),
 ('Population', 4.6035803148689556e-08),
 ('Children', -1.1259363629390848e-07),
 ('Age', -0.00030054449625991335),
 ('Income', 1.4060066471657157e-08),
 ('Outage_sec_perweek', -5.537929299361105e-08),
 ('Email', -1.7244990362663512e-08),
 ('Contacts', 0.0),
 ('Yearly_equip_failure', -4.0765161139922134e-07),
 ('MonthlyCharge', 2.3463690671619955e-05),
 ('Bandwidth_GB_Year', 2.75498127334581e-09),
 ('Item1', 0.0),
 ('Item2', -2.0173997397269452e-08),
 ('Item3', 1.5338451315157345e-08),
 ('Item4', 0.0),
 ('Item5', -4.493897274746188e-09),
 ('Item6', -1.5338451315157345e-08),
 ('Item7', -2.0173997397269452e-08),
 ('Item8', -1.3272551683075974e-08),
 ('StreamingTV_Yes', 7.246295879136567e-09),
 ('StreamingMovies_Yes', -8.622495181331756e-09),
 ('Gender_Male', 0.0),
 ('Gender_Nonbinary', 1.1894751702092201e-08),
 ('PaymentMethod_Credit Card (automatic)', 0.0),
 ('PaymentMethod_Electronic Check', -8.622495181331756e-09),
 ('PaymentMethod_Mailed Check', -1.3272551683075974e-08),
 ('InternetService_Fiber Optic', 0.0),
 ('InternetService_None', 0.0),
 ('Contract_One year', 1.1894751702092201e-08),
 ('Contract_Two Year', -8.622495181331756e-09),
 ('Area_Suburban', 7.246295879136567e-09),
 ('Area_Urban', 7.246295879136567e-09),
 ('Techie_Yes', 4.3044059974068355e-09),
 ('Port_modem_Yes', -5.681405638996317e-09),
 ('Tablet_Yes', 7.246295879136567e-09),
 ('Phone_Yes', 7.246295879136567e-09),
 ('Multiple_Yes', -5.681405638996317e-09),
 ('OnlineSecurity_Yes', 0.0),
```

```
 ('OnlineSecurity_Yes', 0.0),
 ('OnlineBackup_Yes', 0.0),
 ('DeviceProtection_Yes', -8.622495181331756e-09),
 ('TechSupport_Yes', 7.246295879136567e-09),
 ('PaperlessBilling_Yes', -5.681405638996317e-09),
 ('Marital_Married', 0.0),
 ('Marital_Never Married', -8.622495181331756e-09),
 ('Marital_Separated', 1.1894751702092201e-08)]
```

We are having Difficulties retreiving the P-Values from the OLS Model. The cause could be our method of obtaining dummy variables. We needed to encode categorical variables into dummy variables for them to be formatted for our Mulitple Linear Regresssion Model. We cannot perform backwards selection without P-values. Therefore we will try another method of creating dummy variables and obtaining p-values. We also cannot address interpretation of coefficients until appropriate structure and organization/accuracy is achieved.

We can however gain some insight from our initial model. As we can see our dummy variables are adding significantly more variables to our data, for an efficient model we will drop the dummy variables that will be more detrimental than beneficial. This will include variables like county, which is creating a new variable for every single county. We will also drop our target variable Tenure. Additionaly we will drop Interaction, Customer_id, UID, and Churn. These will not continue to our models prediciton of Tenure.

Variables Dropped in 2nd Model - Tenure, Interaction, Customer_id, UID, Area, Job, City, County, TimeZone, State, Churn

Second Model- New Strategy for OLS and P-value for Feature Reduction

In [21]:

```
df_copy3.head()
```

Out[21]:

	CaseOrder	Customer_id	Interaction	UID	City	State	County	Zip	Lat
0	1	K409198	aa90260b-4141-4a24-8e36-b04ce1f4f77b	e885b299883d4f9fb18e39c75155d990	Point Baker	AK	Prince of Wales-Hyder	99927	56.25100
1	2	S120509	fb76459f-c047-4a9d-8af9-e0f7d4ac2524	f2de8bef964785f41a2959829830fb8a	West Branch	MI	Ogemaw	48661	44.32893
2	3	K191035	344d114c-3736-4be5-98f7-c72c281e2d35	f1784cfa9f6d92ae816197eb175d3c71	Yamhill	OR	Yamhill	97148	45.35589
3	4	D90850	abfa2b40-2d43-4994-b15a-989b8c79e311	dc8a365077241bb5cd5ccd305136b05e	Del Mar	CA	San Diego	92014	32.96687
4	5	K662701	68a861fd-0d20-4e51-a587-8a90407ee574	aabb64a116e83fdc4befc1fbab1663f9	Needville	TX	Fort Bend	77461	29.38012

Pre-processing and creating Dummy variables method 2. We are using sklearn's LabelEncoder to pre-process the variables. We will fit them using the lambdha function before we fit them to the model after the test train split

In [22]:

```
# Categorical boolean mask
categorical_feature_mask = df_copy3.dtypes==object
# filter categorical columns using mask and turn it into a list
```

```
categorical_cols = df_copy3.columns[categorical_feature_mask].tolist()
```

In [23]:

```
# import labelencoder
from sklearn.preprocessing import LabelEncoder
# instantiate labelencoder object
le = LabelEncoder()
```

In [24]:

```
# apply le on categorical feature columns
df_copy3[categorical_cols] = df_copy3[categorical_cols].apply(lambda col: le.fit_transform
(col))
```

In [25]:

```
X=df_copy3.drop(["Tenure","Interaction","Customer_id","UID","Area","Job","City","County","
TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [26]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [27]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9986063818158079
```

In [28]:

```
predictions = lm.predict(X_test)
def regression_results(y_true, y_pred):

    # Regression metrics
    explained_variance=metrics.explained_variance_score(y_true, y_pred)
    mean_absolute_error=metrics.mean_absolute_error(y_true, y_pred)
    mse=metrics.mean_squared_error(y_true, y_pred)
   # mean_squared_log_error=metrics.mean_squared_log_error(y_true, y_pred)
    median_absolute_error=metrics.median_absolute_error(y_true, y_pred)
    r2=metrics.r2_score(y_true, y_pred)

    print('explained_variance: ', round(explained_variance,4))
    #print('mean_squared_log_error: ', round(mean_squared_log_error,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))

regression_results(y_test, predictions)
```

```
explained_variance:  0.9986
r2:  0.9986
MAE:  0.8007
MSE:  0.9659
RMSE:  0.9828
```

In [29]:

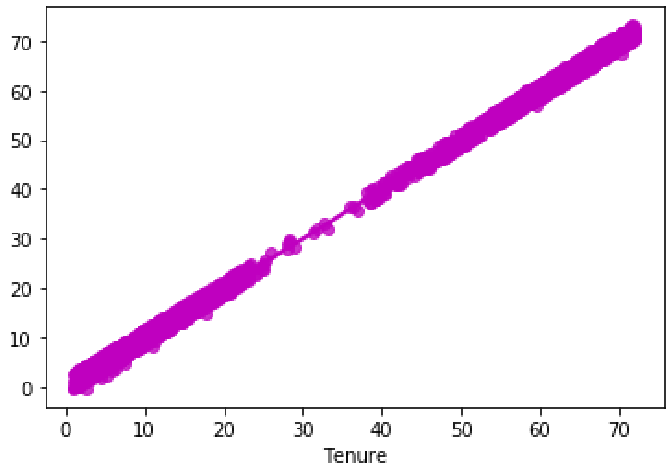
```
residuals = y_test - predictions
```

In [30]:

```
sns.regplot(x=y_test, y=predictions, ci=None, color="m")
```

Out[30]:

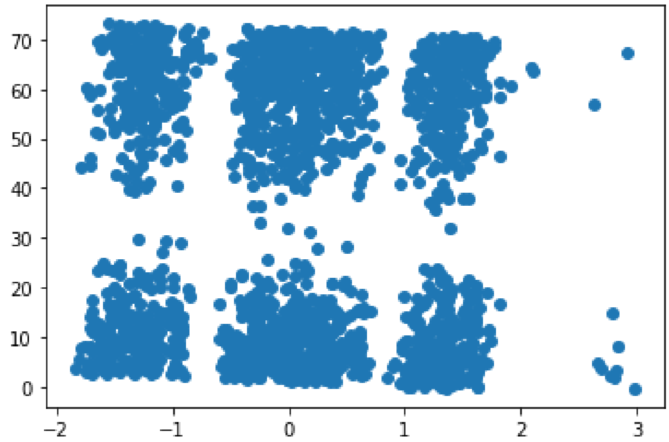
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb5ffbb1b90>
```



In [31]:

```
plt.scatter(residuals,predictions)

plt.show()
```



In [32]:

```
X_train = np.append (arr=np.ones([X_train.shape[0],1]).astype(int), values = X_train, axi
s = 1)
```

In [33]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 39 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   CaseOrder             10000 non-null  int64
 1   Zip                   10000 non-null  int64
 2   Lat                   10000 non-null  float64
 3   Lng                   10000 non-null  float64
 4   Population            10000 non-null  int64
 5   Children              10000 non-null  int64
 6   Age                   10000 non-null  int64
 7   Income                10000 non-null  float64
 8   Marital               10000 non-null  int64
 9   Gender                10000 non-null  int64
 10  Outage_sec_perweek    10000 non-null  float64
 11  Email                 10000 non-null  int64
 12  Contacts              10000 non-null  int64
 13  Yearly_equip_failure  10000 non-null  int64
 14  Techie                10000 non-null  int64
 15  Contract              10000 non-null  int64
 16  Port_modem            10000 non-null  int64
 17  Tablet                10000 non-null  int64
 18  InternetService       10000 non-null  int64
```

```
 19  Phone                10000 non-null  int64
 20  Multiple             10000 non-null  int64
 21  OnlineSecurity       10000 non-null  int64
 22  OnlineBackup         10000 non-null  int64
 23  DeviceProtection     10000 non-null  int64
 24  TechSupport          10000 non-null  int64
 25  StreamingTV          10000 non-null  int64
 26  StreamingMovies      10000 non-null  int64
 27  PaperlessBilling     10000 non-null  int64
 28  PaymentMethod        10000 non-null  int64
 29  MonthlyCharge        10000 non-null  float64
 30  Bandwidth_GB_Year    10000 non-null  float64
 31  Item1                10000 non-null  int64
 32  Item2                10000 non-null  int64
 33  Item3                10000 non-null  int64
 34  Item4                10000 non-null  int64
 35  Item5                10000 non-null  int64
 36  Item6                10000 non-null  int64
 37  Item7                10000 non-null  int64
 38  Item8                10000 non-null  int64
dtypes: float64(6), int64(33)
memory usage: 3.0 MB
```

In [34]:

```python
import statsmodels.api as sm
```

In [35]:

```python
X_opt = [0,1,2,3,4,5,6,7,8,9,10,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,26,27,28,29
,30,31,32,33,34,35,36,37,38]
regressor = sm.OLS(y_train, X_train[:,X_opt]).fit()
print(regressor.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Tenure   R-squared:                       0.999
Model:                            OLS   Adj. R-squared:                  0.999
Method:                 Least Squares   F-statistic:                 1.486e+05
Date:                Mon, 30 Aug 2021   Prob (F-statistic):               0.00
Time:                        00:08:22   Log-Likelihood:                -11297.
No. Observations:                8000   AIC:                         2.267e+04
Df Residuals:                    7961   BIC:                         2.294e+04
Df Model:                          38
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const        -11.1339      0.193    -57.695      0.000     -11.512     -10.756
x1          3.005e-05   6.98e-06      4.307      0.000    1.64e-05    4.37e-05
x2          8.641e-08   9.78e-07      0.088      0.930   -1.83e-06       2e-06
x3             0.0027      0.002      1.209      0.227      -0.002       0.007
x4             0.0007      0.002      0.366      0.715      -0.003       0.004
x5         -4.695e-07   7.94e-07     -0.591      0.554   -2.03e-06    1.09e-06
x6            -0.3761      0.005    -72.537      0.000      -0.386      -0.366
x7             0.0393      0.001     72.966      0.000       0.038       0.040
x8         -3.346e-07      4e-07     -0.836      0.403   -1.12e-06     4.5e-07
x9             0.0033      0.008      0.425      0.671      -0.012       0.019
x10           -0.5757      0.021    -28.061      0.000      -0.616      -0.535
x11            0.0029      0.004      0.775      0.438      -0.004       0.010
x12            0.0007      0.004      0.202      0.840      -0.007       0.008
x13            0.0032      0.011      0.285      0.776      -0.019       0.025
x14            0.0134      0.017      0.766      0.443      -0.021       0.048
x15           -0.0351      0.030     -1.181      0.238      -0.093       0.023
x16           -0.0048      0.013     -0.360      0.719      -0.031       0.021
x17            0.0259      0.022      1.159      0.246      -0.018       0.070
x18            0.0171      0.024      0.703      0.482      -0.031       0.065
x19            2.9843      0.016    191.773      0.000       2.954       3.015
x20            0.0423      0.038      1.111      0.267      -0.032       0.117
x21           -2.6318      0.032    -81.117      0.000      -2.695      -2.568
x22           -1.0755      0.023    -46.023      0.000      -1.121      -1.030
x23           -2.3376      0.028    -84.290      0.000      -2.392      -2.283
x24           -1.7139      0.024    -70.816      0.000      -1.761      -1.667
```

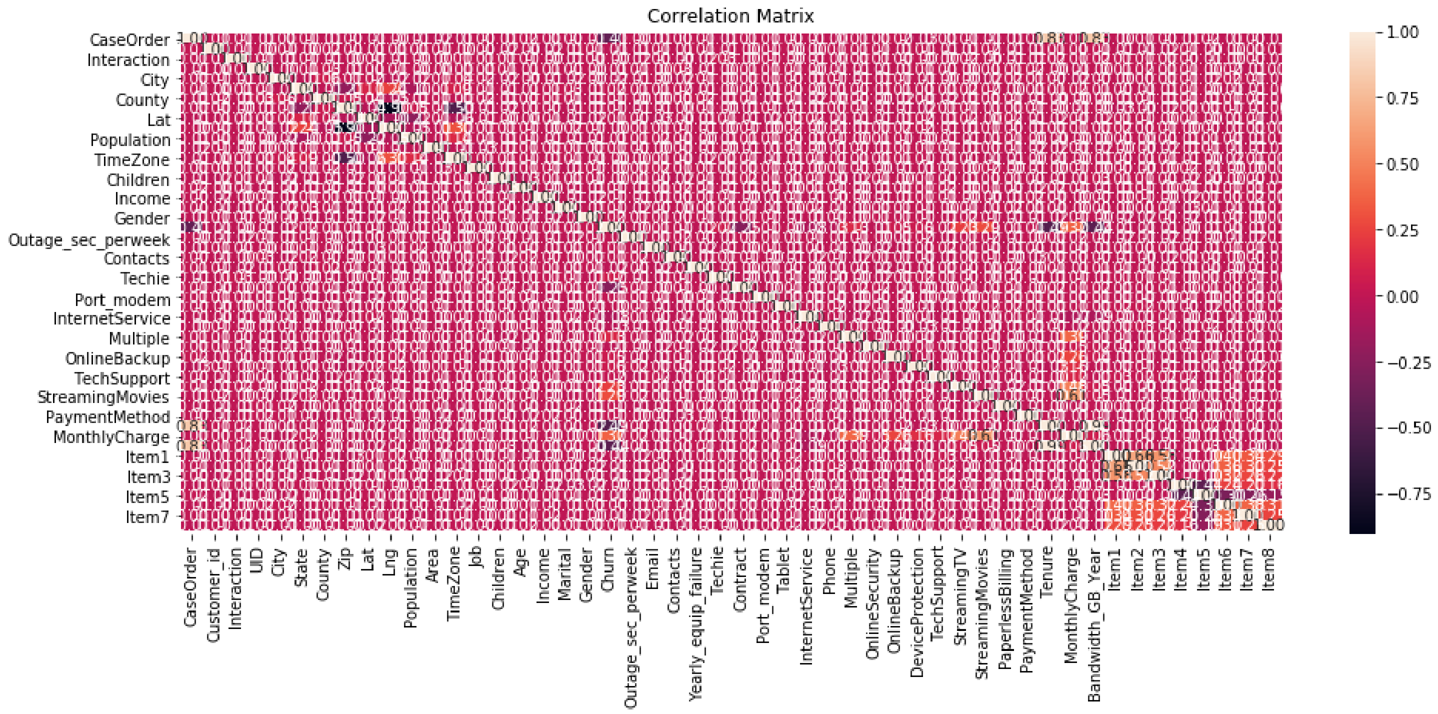
```
x24            -1.7139      0.024    -70.816      0.000      -1.761      -1.667
x25            -0.7639      0.025    -31.129      0.000      -0.812      -0.716
x26            -5.0641      0.038   -134.341      0.000      -5.138      -4.990
x27            -5.3881      0.044   -122.609      0.000      -5.474      -5.302
x28             0.0023      0.023      0.101      0.919      -0.042       0.047
x29             0.0049      0.010      0.469      0.639      -0.016       0.025
x30             0.0542      0.001     75.462      0.000       0.053       0.056
x31             0.0122   9.27e-06   1310.622      0.000       0.012       0.012
x32             0.0502      0.016      3.148      0.002       0.019       0.082
x33            -0.0316      0.015     -2.118      0.034      -0.061      -0.002
x34            -0.0186      0.014     -1.357      0.175      -0.046       0.008
x35             0.0034      0.012      0.277      0.782      -0.021       0.027
x36            -0.0049      0.013     -0.384      0.701      -0.030       0.020
x37             0.0098      0.013      0.752      0.452      -0.016       0.035
x38            -0.0069      0.012     -0.559      0.576      -0.031       0.017
==============================================================================
Omnibus:                      612.667   Durbin-Watson:                   1.960
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              218.508
Skew:                           0.122   Prob(JB):                     3.56e-48
Kurtosis:                       2.228   Cond. No.                     1.22e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified
.
[2] The condition number is large, 1.22e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Our OLS Model is successful in showing our P-values with our new method of creating dummy variables. We will consider this our new Initial Model. We can observe that our model is giving us and output r2 of 0.9986. This tells us that our model is accurate, the regplot shows us the residuals are falling along the prediciton line, this is good affirmation of the model as well. However when we look at the residual scatter plot we can see a discernable pattern. The residuals are grouped in 6 distinct groups, this could mean that the data is skewed or biased in some way, some of the input variables could be impacting each other. We will remedy this by checking for Multicollinearity. We will continue with a Correlation Matrix Heatmap, then Backwards Selection

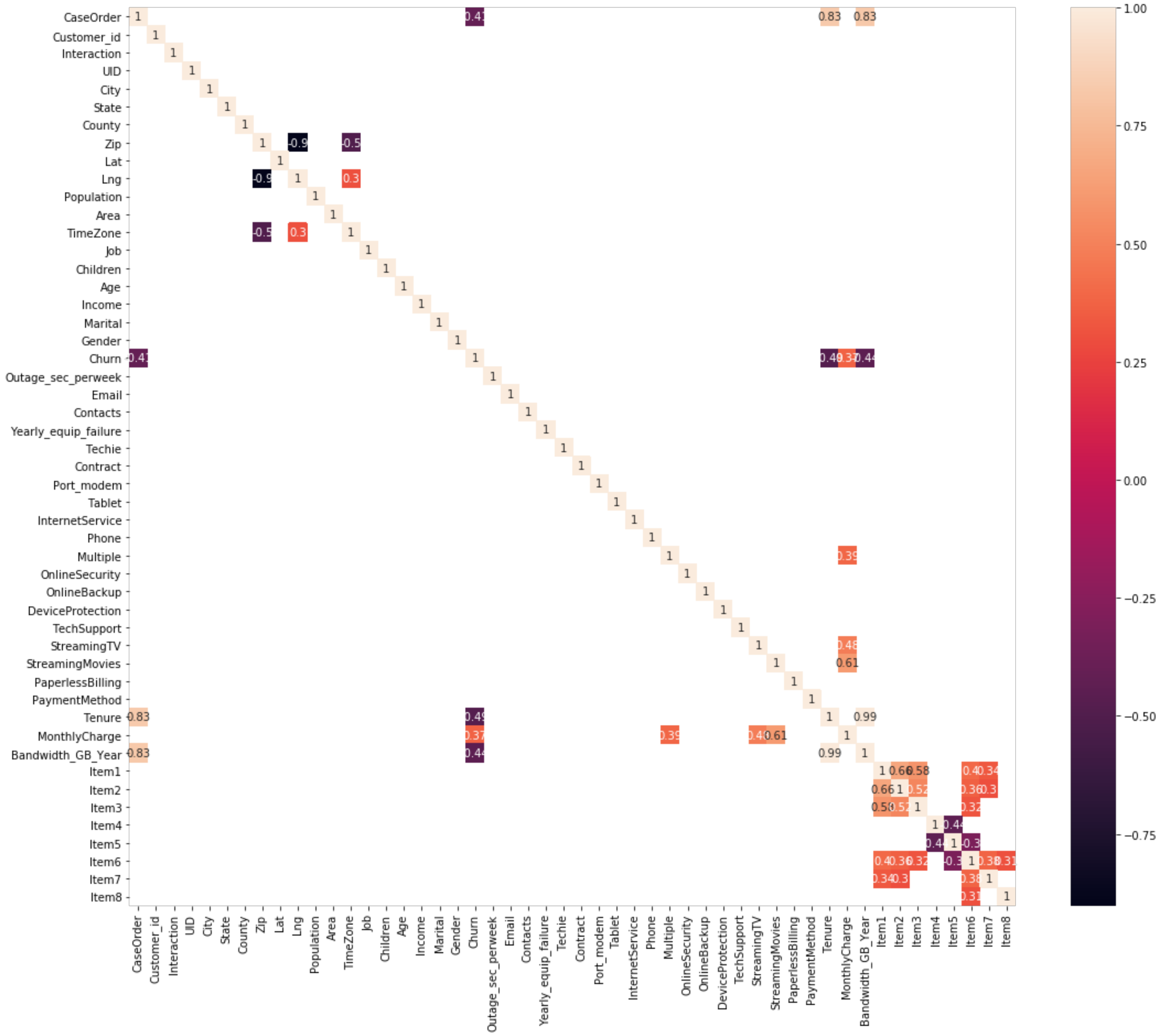
In [36]:

```
plt.figure(figsize=(16, 6))
ax = sns.heatmap(df_copy4.corr(), annot=True, fmt='.2f') # Plot of the correlation matrix
bottom, top = ax.get_ylim() # Figure limits
ax.set_ylim(bottom+0.3, top-0.3) # Setting figure limits
plt.title('Correlation Matrix') # Figure title
plt.show()
```



In [37]:

```
corr= df_copy4.corr() # Redifining the correlation matrix.
f,ax = plt.subplots(figsize=(18, 15)) # Set the figure size.
sns.heatmap(corr[(corr >= 0.30) | (corr <= -0.30)],
            annot=True); # Figure of the correlation matrix with variables removal
```



We will drop Item7, Item1, Outages_sec_perweek,and StreamingMovies because they could cause possible Multicollinearity

Backward Selection

We will Take all the variables with a P-Value above our significance level, .05,out of our dataframe. We will repeat this Process until there are only statistically significant variables left to optimize our Model

x37, x10, x26 dropped first

In [38]:

```
X_opt = [0,1,2,3,4,5,6,7,8,9,11,12,13,14,15,16,17,18,19,20,21,22,23,24,25,27,28,29,30,31
,32,33,34,35,36,38]
regressor = sm.OLS(y_train, X_train[:,X_opt]).fit()
print(regressor.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Tenure   R-squared:                       0.995
Model:                            OLS   Adj. R-squared:                  0.995
Method:                 Least Squares   F-statistic:                 4.744e+04
Date:                Mon, 30 Aug 2021   Prob (F-statistic):               0.00
Time:                        00:08:34   Log-Likelihood:                -16181.
No. Observations:                8000   AIC:                         3.243e+04
Df Residuals:                    7964   BIC:                         3.269e+04
Df Model:                          35
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -5.1297      0.340    -15.093      0.000      -5.796      -4.463
x1             0.0001   1.28e-05      8.474      0.000    8.34e-05       0.000
x2         -1.318e-06    1.8e-06     -0.732      0.464   -4.85e-06    2.21e-06
x3            -0.0010      0.004     -0.238      0.812      -0.009       0.007
x4            -0.0005      0.003     -0.167      0.867      -0.007       0.006
x5          -1.42e-06   1.46e-06     -0.972      0.331   -4.29e-06    1.44e-06
x6            -0.3701      0.010    -38.771      0.000      -0.389      -0.351
x7             0.0393      0.001     39.649      0.000       0.037       0.041
x8         -2.852e-08   7.37e-07     -0.039      0.969   -1.47e-06    1.42e-06
x9             0.0033      0.014      0.231      0.817      -0.025       0.031
x10            0.0035      0.007      0.503      0.615      -0.010       0.017
x11           -0.0019      0.007     -0.274      0.784      -0.015       0.012
x12            0.0319      0.021      1.541      0.123      -0.009       0.073
x13           -0.0364      0.032     -1.131      0.258      -0.099       0.027
x14            0.0093      0.055      0.171      0.864      -0.098       0.117
x15            0.0028      0.025      0.113      0.910      -0.045       0.051
x16            0.0054      0.041      0.133      0.894      -0.075       0.086
x17           -0.0474      0.045     -1.058      0.290      -0.135       0.040
x18            2.6758      0.028     94.446      0.000       2.620       2.731
x19           -0.0095      0.070     -0.135      0.892      -0.147       0.128
x20           -0.1097      0.049     -2.252      0.024      -0.205      -0.014
x21           -0.8320      0.043    -19.405      0.000      -0.916      -0.748
x22           -0.5539      0.045    -12.365      0.000      -0.642      -0.466
x23           -0.7546      0.043    -17.735      0.000      -0.838      -0.671
x24            0.1652      0.043      3.809      0.000       0.080       0.250
x25           -1.2846      0.058    -22.118      0.000      -1.399      -1.171
x26            0.1020      0.042      2.443      0.015       0.020       0.184
x27            0.0146      0.019      0.762      0.446      -0.023       0.052
x28           -0.0234      0.001    -29.715      0.000      -0.025      -0.022
x29            0.0120    1.7e-05    707.992      0.000       0.012       0.012
x30            0.0781      0.029      2.702      0.007       0.021       0.135
x31           -0.0073      0.027     -0.268      0.788      -0.061       0.046
x32           -0.0380      0.025     -1.512      0.131      -0.087       0.011
x33            0.0115      0.022      0.513      0.608      -0.032       0.055
x34            0.0167      0.023      0.724      0.469      -0.028       0.062
x35           -0.0115      0.022     -0.515      0.607      -0.055       0.032
==============================================================================
Omnibus:                     2180.714   Durbin-Watson:                   2.009
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              377.751
Skew:                           0.133   Prob(JB):                     9.38e-83
Kurtosis:                       1.969   Cond. No.                     1.16e+06
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified
.
[2] The condition number is large, 1.16e+06. This might indicate that there are
strong multicollinearity or other numerical problems.
```

Final Backward Selection Model

In [39]:

```
X_opt = [0,1,6,7,19,22,23,24,25,27,28,30,31,32]
regressor = sm.OLS(y_train, X_train[:,X_opt]).fit()
print(regressor.summary())
```

```
                            OLS Regression Results
==============================================================================
Dep. Variable:                 Tenure   R-squared:                       0.995
Model:                            OLS   Adj. R-squared:                  0.995
Method:                 Least Squares   F-statistic:                 1.278e+05
Date:                Mon, 30 Aug 2021   Prob (F-statistic):               0.00
Time:                        00:08:34   Log-Likelihood:                -16190.
No. Observations:                8000   AIC:                         3.241e+04
Df Residuals:                    7986   BIC:                         3.251e+04
Df Model:                          13
Covariance Type:            nonrobust
==============================================================================
                 coef    std err          t      P>|t|      [0.025      0.975]
------------------------------------------------------------------------------
const         -5.0853      0.139    -36.565      0.000      -5.358      -4.813
x1             0.0001   1.28e-05      8.460      0.000    8.31e-05       0.000
x2            -0.3697      0.010    -38.781      0.000      -0.388      -0.351
x3             0.0393      0.001     39.727      0.000       0.037       0.041
x4             2.6733      0.028     94.568      0.000       2.618       2.729
x5            -0.8266      0.043    -19.328      0.000      -0.910      -0.743
x6            -0.5314      0.044    -12.149      0.000      -0.617      -0.446
x7            -0.7402      0.042    -17.552      0.000      -0.823      -0.658
x8             0.1749      0.043      4.068      0.000       0.091       0.259
x9            -1.2385      0.054    -22.967      0.000      -1.344      -1.133
x10            0.1011      0.042      2.426      0.015       0.019       0.183
x11           -0.0242      0.001    -36.539      0.000      -0.026      -0.023
x12            0.0120     1.7e-05    708.981      0.000       0.012       0.012
x13            0.0470      0.020      2.376      0.018       0.008       0.086
==============================================================================
Omnibus:                     2437.416   Durbin-Watson:                   2.008
Prob(Omnibus):                  0.000   Jarque-Bera (JB):              393.187
Skew:                           0.138   Prob(JB):                     4.17e-86
Kurtosis:                       1.950   Cond. No.                     4.79e+04
==============================================================================

Warnings:
[1] Standard Errors assume that the covariance matrix of the errors is correctly specified
.
[2] The condition number is large, 4.79e+04. This might indicate that there are
strong multicollinearity or other numerical problems.
```

In [40]:

```
X=df_copy4.drop(["Tenure","Lat","Lng","Population","Children","Marital","Gender","Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Contract","Port_modem","Tablet","InternetService","Multiple","OnlineSecurity","StreamingMovies","MonthlyCharge","Item3","Item4","Item5","Item6","Item7","Item8"], axis=1)
Y=df["Tenure"]
```

In [41]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 24 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   CaseOrder             10000 non-null  int64  
 1   Customer_id           10000 non-null  int64  
 2   Interaction           10000 non-null  int64  
 3   UID                   10000 non-null  int64  
 4   City                  10000 non-null  int64  
 5   State                 10000 non-null  int64  
 6   County                10000 non-null  int64  
 7   Zip                   10000 non-null  int64  
 8   Area                  10000 non-null  int64  
 9   TimeZone              10000 non-null  int64  
 10  Job                   10000 non-null  int64  
 11  Age                   10000 non-null  int64  
 12  Income                10000 non-null  float64
 13  Churn                 10000 non-null  int64  
 14  Phone                 10000 non-null  int64  
```

```
 14  Phone               10000 non-null  int64
 15  OnlineBackup        10000 non-null  int64
 16  DeviceProtection    10000 non-null  int64
 17  TechSupport         10000 non-null  int64
 18  StreamingTV         10000 non-null  int64
 19  PaperlessBilling    10000 non-null  int64
 20  PaymentMethod       10000 non-null  int64
 21  Bandwidth_GB_Year   10000 non-null  float64
 22  Item1               10000 non-null  int64
 23  Item2               10000 non-null  int64
dtypes: float64(2), int64(22)
memory usage: 1.8 MB
```

After dropping the variables with a p-value above the 0.05 threshold we are left with the above 24 variables, they are a mixture of categorical and continious variabes. These will comprise our final model, this model should theoretically be the most accurate

In [42]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [43]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9891169893383468
```

In [44]:

```
predictions = lm.predict(X_test)
def regression_results(y_true, y_pred):

    # Regression metrics
    explained_variance=metrics.explained_variance_score(y_true, y_pred)
    mean_absolute_error=metrics.mean_absolute_error(y_true, y_pred)
    mse=metrics.mean_squared_error(y_true, y_pred)
   # mean_squared_log_error=metrics.mean_squared_log_error(y_true, y_pred)
    median_absolute_error=metrics.median_absolute_error(y_true, y_pred)
    r2=metrics.r2_score(y_true, y_pred)

    print('explained_variance: ', round(explained_variance,4))
    #print('mean_squared_log_error: ', round(mean_squared_log_error,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))

regression_results(y_test, predictions)
```

```
explained_variance:  0.9891
r2:  0.9891
MAE:  2.2869
MSE:  7.5425
RMSE:  2.7464
```

In [45]:

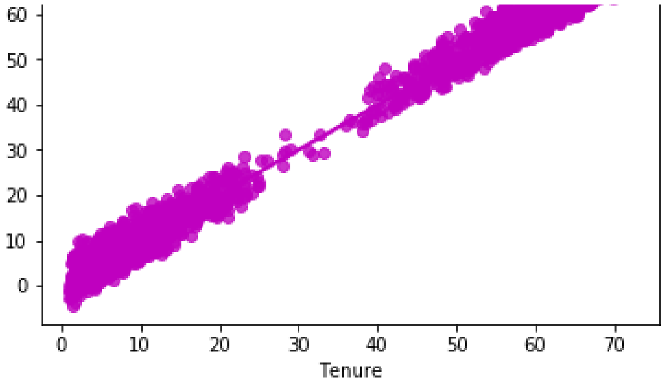
```
residuals = y_test - predictions
```

In [46]:

```
sns.regplot(x=y_test, y=predictions, ci=None, color="m")
```

Out[46]:

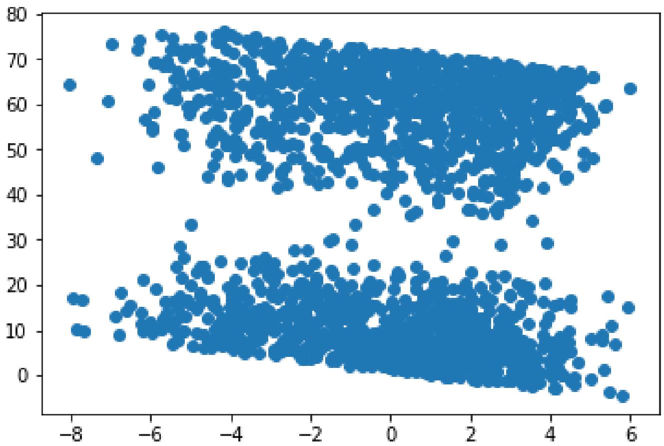
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb5e7eb5950>
```



In [47]:

```
plt.scatter(residuals,predictions)

plt.show()
```



In [ ]:

```

```

Forward Selection

We will start by dropping the same base variables as the backward selection models and the begin by only including the demographic variables. We will then determine which demographic variable should be included in our final reduced model.

In [48]:

```
X=df_copy5.drop(["Tenure","CaseOrder","Customer_id","Interaction","UID","Income","Churn","
Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Port_modem","Contr
act","Tablet","InternetService","Phone","Multiple","OnlineSecurity","OnlineBackup","Device
Protection","TechSupport","StreamingTV","StreamingMovies","PaperlessBilling","PaymentMetho
d","MonthlyCharge","Bandwidth_GB_Year","Item1","Item2","Item3","Item4","Item5","Item6","I
tem7","Item8"], axis=1)
Y=df["Tenure"]
```

In [49]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [50]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

-0.002513173792250356

We've Observed a negative R2 by exluding performance and technology metrics and only inculding demographic variables

In [51]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 14 columns):
 #   Column      Non-Null Count  Dtype  
---  ------      --------------  -----  
 0   City        10000 non-null  int64  
 1   State       10000 non-null  int64  
 2   County      10000 non-null  int64  
 3   Zip         10000 non-null  int64  
 4   Lat         10000 non-null  float64
 5   Lng         10000 non-null  float64
 6   Population  10000 non-null  int64  
 7   Area        10000 non-null  int64  
 8   TimeZone    10000 non-null  int64  
 9   Job         10000 non-null  int64  
 10  Children    10000 non-null  int64  
 11  Age         10000 non-null  int64  
 12  Marital     10000 non-null  int64  
 13  Gender      10000 non-null  int64  
dtypes: float64(2), int64(12)
memory usage: 1.1 MB
```

We will check to see which of these demographic variables is most important and retain only those for our final model. We must keep in mind that the dummy variables that wil drastically increase the number of variables wil not be beneficial to our model and we will not try to incorporate them. We wil intuitively choose the variables that we think are most beneficial and integral. From the above remaining variables we will test Income, Gender, Marital, and Population to see how they impact the model's R2

In [52]:

```
#### Dropping Income
```

In [53]:

```
X=df_copy5.drop(["Income","Tenure","CaseOrder","Customer_id","Interaction","UID","Income",
"Churn","Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Port_mode
m","Contract","Tablet","InternetService","Phone","Multiple","OnlineSecurity","OnlineBackup
","DeviceProtection","TechSupport","StreamingTV","StreamingMovies","PaperlessBilling","Pay
mentMethod","MonthlyCharge","Bandwidth_GB_Year","Item1","Item2","Item3","Item4","Item5","
Item6","Item7","Item8"], axis=1)
Y=df["Tenure"]
```

In [54]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [55]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
-0.002513173792250356
```

No impact

In [ ]:

```

```

Dropping Gender

In [56]:

```
X=df_copy5.drop(["Gender","Income","Tenure","CaseOrder","Customer_id","Interaction","UID","Income","Churn","Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Port_modem","Contract","Tablet","InternetService","Phone","Multiple","OnlineSecurity","OnlineBackup","DeviceProtection","TechSupport","StreamingTV","StreamingMovies","PaperlessBilling","PaymentMethod","MonthlyCharge","Bandwidth_GB_Year","Item1","Item2","Item3","Item4","Item5","Item6","Item7","Item8"], axis=1)
Y=df["Tenure"]
```

In [57]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [58]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
-0.0029906807478796704
```

Dropping Gender decreased our score by .0004, we will consider it significant

In [ ]:

```

```

In [59]:

```
#### Dropping Marital and Population
```

In [60]:

```
X=df_copy5.drop(["Marital","Population","Gender","Income","Tenure","CaseOrder","Customer_id","Interaction","UID","Income","Churn","Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Port_modem","Contract","Tablet","InternetService","Phone","Multiple","OnlineSecurity","OnlineBackup","DeviceProtection","TechSupport","StreamingTV","StreamingMovies","PaperlessBilling","PaymentMethod","MonthlyCharge","Bandwidth_GB_Year","Item1","Item2","Item3","Item4","Item5","Item6","Item7","Item8"], axis=1)
Y=df["Tenure"]
```

In [61]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [62]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
-0.002294580726309059
```

Dropping these variables increased our R2, we will exlude them from the Final Model

We have concluded that out of all the Demographic variables We will include Gender, there is a possibility that Income can tie into other predictor variables and another combination of variables in the final model. We will intuitively decide to keep income in our final model

In [ ]:

```

```

We will now test the performance metrics in forward selection fashion to

We will now test the performance metrics in forward selection fashion to determine which of these variables are significant enough to include in our Final Model. We will start with our base drop statement from our backwards selection and move forward from there.

We will intuitively choose performance metric variables and test them for impact in our regression model. We will choose InternetService,Multiple,OnlineSecurit, OnlineBackup, DeviceProtection, StreamingTV, StreamingMovies, MonthlyCharge, Bandwidth_GB_Year, and the Items. We will exclude a few of the items to decrease possibilty of multicollinearity that we observed could be possible from our Correlation Matrix Heatmap

In [ ]:

```

```

Dropping InternetService

In [63]:

```
X=df_copy6.drop(["InternetService","Tenure","Interaction","Customer_id","UID","Area","Job"
,"City","County","TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [64]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [65]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9920579404425306
```

has negative impact when not included in model when compared to initial backward selection model, has a difference of .005, we will include in our final model

In [ ]:

```

```

Dropping Mulitple

In [66]:

```
X=df_copy6.drop(["Multiple","InternetService","Tenure","Interaction","Customer_id","UID","
Area","Job","City","County","TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [67]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [68]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9914289068373454
```

Has an impact, we will include in final model

In [ ]:

Droppoing Online Security

In [69]:

```
X=df_copy6.drop(["OnlineSecurity","Multiple","InternetService","Tenure","Interaction","Cus
tomer_id","UID","Area","Job","City","County","TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [70]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [71]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9912530574260171
```

Has an impact, we will include in final model

In [ ]:

```

```

Dropping OnlineBackup

In [72]:

```
X=df_copy6.drop(["OnlineBackup","OnlineSecurity","Multiple","InternetService","Tenure","In
teraction","Customer_id","UID","Area","Job","City","County","TimeZone","State","Churn"],
axis=1)
Y=df["Tenure"]
```

In [73]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [74]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9908223077207488
```

Has an impact, we will include in final model

In [ ]:

```

```

Dropping DeviceProtection

In [75]:

```
X=df_copy6.drop(["DeviceProtection","OnlineBackup","OnlineSecurity","Multiple","InternetSe
rvice","Tenure","Interaction","Customer_id","UID","Area","Job","City","County","TimeZone",
"State","Churn"], axis=1)
Y=df["Tenure"]
```

In [76]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [77]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9905373494469566
```

Has an impact, we will include in final model

In [ ]:

```

```

Dropping StreamingTV and StreamingMovies

In [78]:

```
X=df_copy6.drop(["StreamingTV","StreamingMovies","DeviceProtection","OnlineBackup","Online
Security","Multiple","InternetService","Tenure","Interaction","Customer_id","UID","Area","
Job","City","County","TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [79]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [80]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9894164863525595
```

Has an impact, we will include in final model

In [ ]:

```

```

Dropping MonthlyCharge

In [81]:

```
X=df_copy6.drop(["MonthlyCharge","StreamingTV","StreamingMovies","DeviceProtection","Onlin
eBackup","OnlineSecurity","Multiple","InternetService","Tenure","Interaction","Customer_id
","UID","Area","Job","City","County","TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [82]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [83]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9855446518038253
```

Has an impact, we will include in final model

In [ ]:

```

```

Dropping Bandwidth_GB_Year

In [84]:

```
X=df_copy6.drop(["Bandwidth_GB_Year","MonthlyCharge","StreamingTV","StreamingMovies","DeviceProtection","OnlineBackup","OnlineSecurity","Multiple","InternetService","Tenure","Interaction","Customer_id","UID","Area","Job","City","County","TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [85]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [86]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

0.6900707021439811

Has the most significant impact out of all variables in our Model Feature selection. We will definitely include in our final model

In [ ]:

```

```

Dropping Item2-5 and Item7, We believe Items1 and Item7 can cause Multicollinearity

In [87]:

```
X=df_copy6.drop(["Item2","Item3","Item4","Item5","Bandwidth_GB_Year","MonthlyCharge","StreamingTV","StreamingMovies","DeviceProtection","OnlineBackup","OnlineSecurity","Multiple","InternetService","Tenure","Interaction","Customer_id","UID","Area","Job","City","County","TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [88]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [89]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

0.6900279546048143

Has an impact, we will include in final model

In [ ]:

```

```

Final Model with Forward Selected Variables

In [90]:

```
X=df.drop(["Tenure","Interaction","Customer_id","UID","Area","Job","City","County","TimeZone","State","Churn","CaseOrder","Zip","Lng","Lat","Population","Children","Age","CaseOrder","Zip","Lat","Lng","Population","Children","Age","Marital","Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Port_modem","Tablet","Phone","TechSupport","PaperlessBilling","PaymentMethod","Item1","Item6","Item8"], axis=1)
Y=df["Tenure"]
```

In [91]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   Income             10000 non-null  float64
 1   Gender             10000 non-null  int64
 2   Contract           10000 non-null  int64
 3   InternetService    10000 non-null  int64
 4   Multiple           10000 non-null  int64
 5   OnlineSecurity     10000 non-null  int64
 6   OnlineBackup       10000 non-null  int64
 7   DeviceProtection   10000 non-null  int64
 8   StreamingTV        10000 non-null  int64
 9   StreamingMovies    10000 non-null  int64
 10  MonthlyCharge      10000 non-null  float64
 11  Bandwidth_GB_Year  10000 non-null  float64
 12  Item2              10000 non-null  int64
 13  Item3              10000 non-null  int64
 14  Item4              10000 non-null  int64
 15  Item5              10000 non-null  int64
 16  Item7              10000 non-null  int64
dtypes: float64(3), int64(14)
memory usage: 1.3 MB
```

In [92]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [93]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9965911011759179
```

In [94]:

```
predictions = lm.predict(X_test)
def regression_results(y_true, y_pred):

    # Regression metrics
    explained_variance=metrics.explained_variance_score(y_true, y_pred)
    mean_absolute_error=metrics.mean_absolute_error(y_true, y_pred)
    mse=metrics.mean_squared_error(y_true, y_pred)
   # mean_squared_log_error=metrics.mean_squared_log_error(y_true, y_pred)
    median_absolute_error=metrics.median_absolute_error(y_true, y_pred)
    r2=metrics.r2_score(y_true, y_pred)

    print('explained_variance: ', round(explained_variance,4))
    #print('mean_squared_log_error: ', round(mean_squared_log_error,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))

regression_results(y_test, predictions)
```

```
explained_variance:  0.9966
```

```
r2:  0.9966
MAE:  1.2319
MSE:  2.3625
RMSE:  1.5371
```

In [95]:

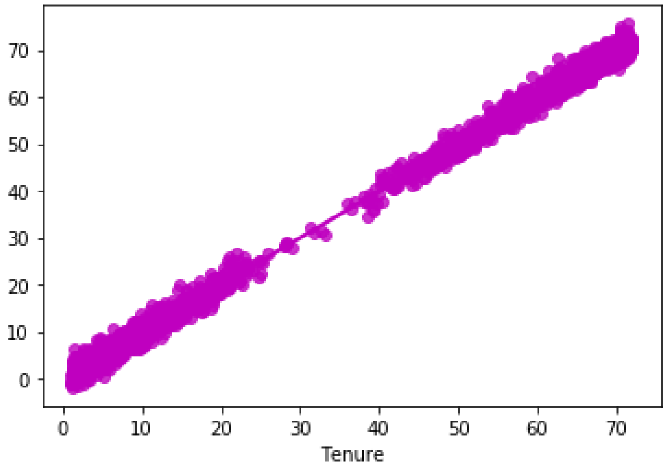
```
residuals = y_test - predictions
```

In [96]:

```
sns.regplot(x=y_test, y=predictions, ci=None, color="m")
```

Out[96]:

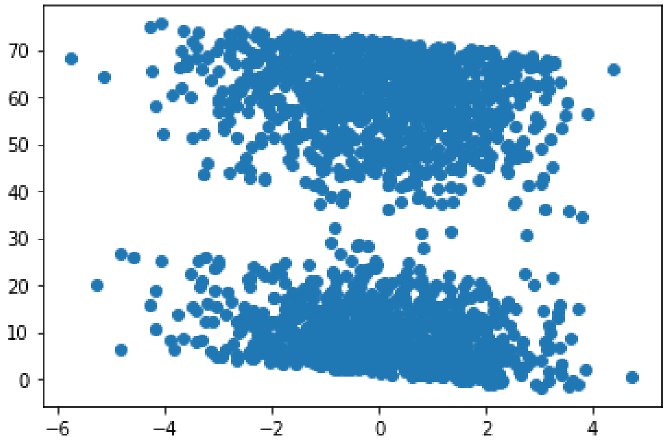
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb5e885b610>
```



In [97]:

```
plt.scatter(residuals,predictions)

plt.show()
```



Final Backward and Forward Selection Model Comparison

Initial Backward Model

In [98]:

```
X=df_copy3.drop(["Tenure","Interaction","Customer_id","UID","Area","Job","City","County","
TimeZone","State","Churn"], axis=1)
Y=df["Tenure"]
```

In [99]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [100]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9986063818158079
```

In [101]:

```
predictions = lm.predict(X_test)
def regression_results(y_true, y_pred):

    # Regression metrics
    explained_variance=metrics.explained_variance_score(y_true, y_pred)
    mean_absolute_error=metrics.mean_absolute_error(y_true, y_pred)
    mse=metrics.mean_squared_error(y_true, y_pred)
   # mean_squared_log_error=metrics.mean_squared_log_error(y_true, y_pred)
    median_absolute_error=metrics.median_absolute_error(y_true, y_pred)
    r2=metrics.r2_score(y_true, y_pred)

    print('explained_variance: ', round(explained_variance,4))
    #print('mean_squared_log_error: ', round(mean_squared_log_error,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))

regression_results(y_test, predictions)
```

```
explained_variance:  0.9986
r2:  0.9986
MAE:  0.8007
MSE:  0.9659
RMSE:  0.9828
```

In [102]:

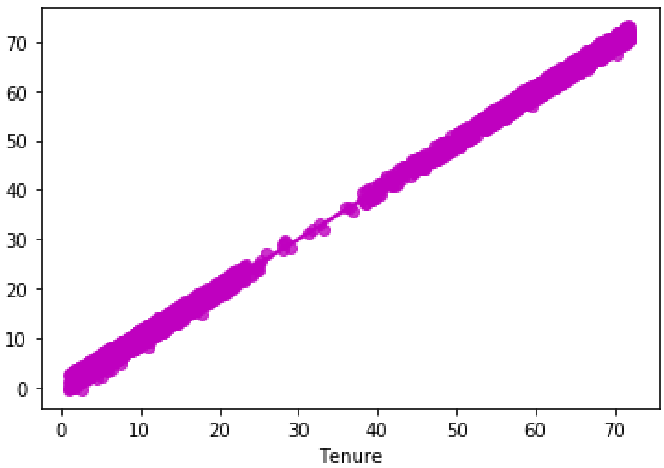
```
residuals = y_test - predictions
```

In [103]:

```
sns.regplot(x=y_test, y=predictions, ci=None, color="m")
```

Out[103]:

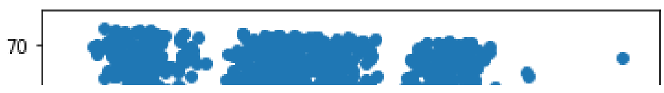
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb5e86a2310>
```

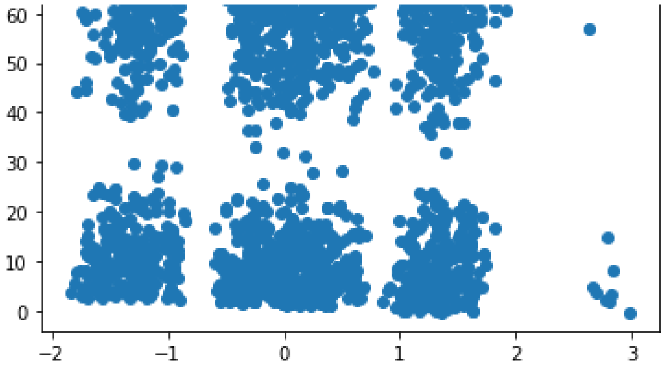


In [104]:

```
plt.scatter(residuals,predictions)

plt.show()
```





In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

Final Backward Model

In [105]:

```
X=df_copy4.drop(["Tenure","Lat","Lng","Population","Children","Marital","Gender","Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Contract","Port_modem","Tablet","InternetService","Multiple","OnlineSecurity","StreamingMovies","MonthlyCharge","Item3","Item4","Item5","Item6","Item7","Item8"], axis=1)
Y=df["Tenure"]
```

In [106]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 24 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   CaseOrder           10000 non-null  int64  
 1   Customer_id         10000 non-null  int64  
 2   Interaction         10000 non-null  int64  
 3   UID                 10000 non-null  int64  
 4   City                10000 non-null  int64  
 5   State               10000 non-null  int64  
 6   County              10000 non-null  int64  
 7   Zip                 10000 non-null  int64  
 8   Area                10000 non-null  int64  
 9   TimeZone            10000 non-null  int64  
 10  Job                 10000 non-null  int64  
 11  Age                 10000 non-null  int64  
 12  Income              10000 non-null  float64
 13  Churn               10000 non-null  int64  
 14  Phone               10000 non-null  int64  
 15  OnlineBackup        10000 non-null  int64  
 16  DeviceProtection    10000 non-null  int64  
 17  TechSupport         10000 non-null  int64  
 18  StreamingTV         10000 non-null  int64  
 19  PaperlessBilling    10000 non-null  int64  
 20  PaymentMethod       10000 non-null  int64  
 21  Bandwidth_GB_Year   10000 non-null  float64
 22  Item1               10000 non-null  int64  
 23  Item2               10000 non-null  int64  
dtypes: float64(2), int64(22)
memory usage: 1.8 MB
```

In [107]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [108]:

```
lm = LinearRegression()
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9891169893383468
```

In [109]:

```
predictions = lm.predict(X_test)
def regression_results(y_true, y_pred):

    # Regression metrics
    explained_variance=metrics.explained_variance_score(y_true, y_pred)
    mean_absolute_error=metrics.mean_absolute_error(y_true, y_pred)
    mse=metrics.mean_squared_error(y_true, y_pred)
   # mean_squared_log_error=metrics.mean_squared_log_error(y_true, y_pred)
    median_absolute_error=metrics.median_absolute_error(y_true, y_pred)
    r2=metrics.r2_score(y_true, y_pred)

    print('explained_variance: ', round(explained_variance,4))
    #print('mean_squared_log_error: ', round(mean_squared_log_error,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))

regression_results(y_test, predictions)
```

```
explained_variance:  0.9891
r2:  0.9891
MAE:  2.2869
MSE:  7.5425
RMSE:  2.7464
```

In [110]:

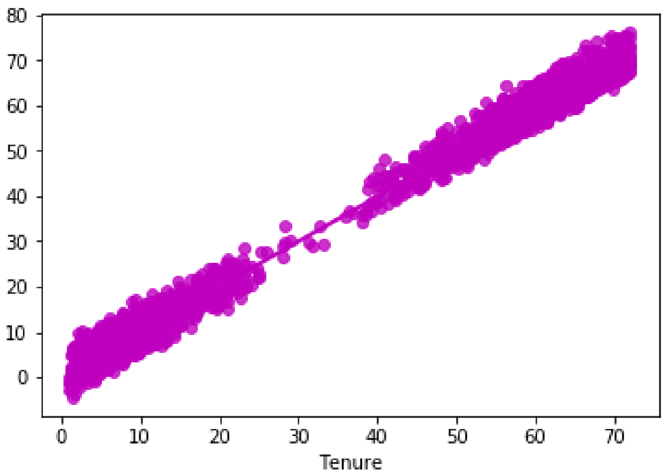
```
residuals = y_test - predictions
```

In [111]:

```
sns.regplot(x=y_test, y=predictions, ci=None, color="m")
```

Out[111]:

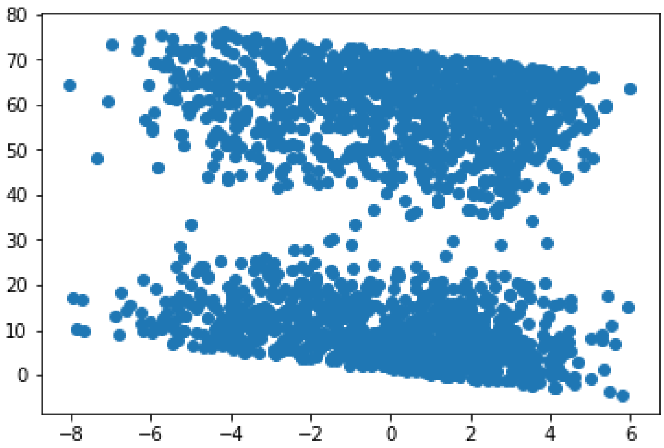
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb5e93ed910>
```



In [112]:

```
plt.scatter(residuals,predictions)
```

```
plt.show()
```



In [ ]:

```

```

Forward Model

In [113]:

```
X=df_copy7.drop(["Tenure","Interaction","Customer_id","UID","Area","Job","City","County","TimeZone","State","Churn","CaseOrder","Zip","Lng","Lat","Population","Children","Age","CaseOrder","Zip","Lat","Lng","Population","Children","Age","Marital","Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Port_modem","Tablet","Phone","TechSupport","PaperlessBilling","PaymentMethod","Item1","Item6","Item8"], axis=1)
Y=df["Tenure"]
```

In [114]:

```
X.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 17 columns):
 #   Column              Non-Null Count  Dtype  
---  ------              --------------  -----  
 0   Income              10000 non-null  float64
 1   Gender              10000 non-null  int64  
 2   Contract            10000 non-null  int64  
 3   InternetService     10000 non-null  int64  
 4   Multiple            10000 non-null  int64  
 5   OnlineSecurity      10000 non-null  int64  
 6   OnlineBackup        10000 non-null  int64  
 7   DeviceProtection    10000 non-null  int64  
 8   StreamingTV         10000 non-null  int64  
 9   StreamingMovies     10000 non-null  int64  
 10  MonthlyCharge       10000 non-null  float64
 11  Bandwidth_GB_Year   10000 non-null  float64
 12  Item2               10000 non-null  int64  
 13  Item3               10000 non-null  int64  
 14  Item4               10000 non-null  int64  
 15  Item5               10000 non-null  int64  
 16  Item7               10000 non-null  int64  
dtypes: float64(3), int64(14)
memory usage: 1.3 MB
```

In [115]:

```
X_train, X_test, y_train, y_test = train_test_split(X, Y, test_size=0.2, random_state=4)
```

In [116]:

```
lm = LinearRegression()
```

```
lm.fit(X_train,y_train)
print(lm.score(X_test,y_test))
```

```
0.9965911011759179
```

In [117]:

```
predictions = lm.predict(X_test)
def regression_results(y_true, y_pred):

    # Regression metrics
    explained_variance=metrics.explained_variance_score(y_true, y_pred)
    mean_absolute_error=metrics.mean_absolute_error(y_true, y_pred)
    mse=metrics.mean_squared_error(y_true, y_pred)
   # mean_squared_log_error=metrics.mean_squared_log_error(y_true, y_pred)
    median_absolute_error=metrics.median_absolute_error(y_true, y_pred)
    r2=metrics.r2_score(y_true, y_pred)

    print('explained_variance: ', round(explained_variance,4))
    #print('mean_squared_log_error: ', round(mean_squared_log_error,4))
    print('r2: ', round(r2,4))
    print('MAE: ', round(mean_absolute_error,4))
    print('MSE: ', round(mse,4))
    print('RMSE: ', round(np.sqrt(mse),4))

regression_results(y_test, predictions)
```

```
explained_variance:  0.9966
r2:  0.9966
MAE:  1.2319
MSE:  2.3625
RMSE:  1.5371
```

In [118]:

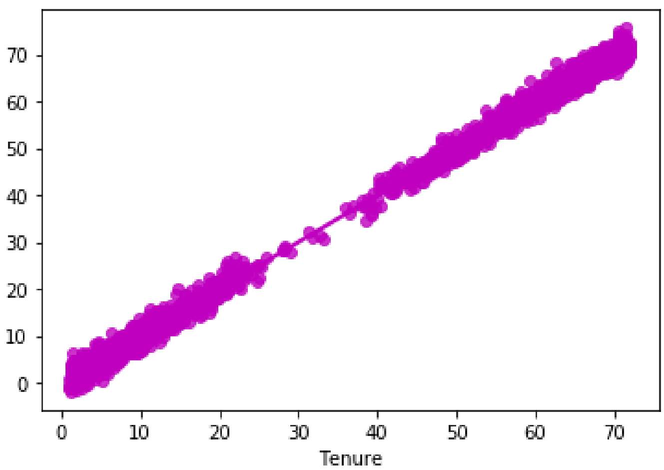
```
residuals = y_test - predictions
```

In [119]:

```
sns.regplot(x=y_test, y=predictions, ci=None, color="m")
```

Out[119]:

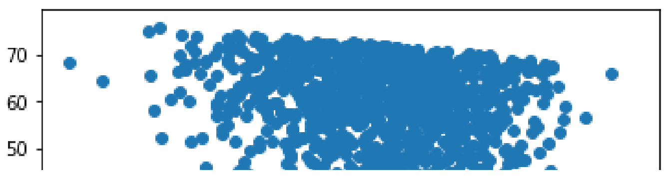
```
<matplotlib.axes._subplots.AxesSubplot at 0x7fb5e89a0090>
```

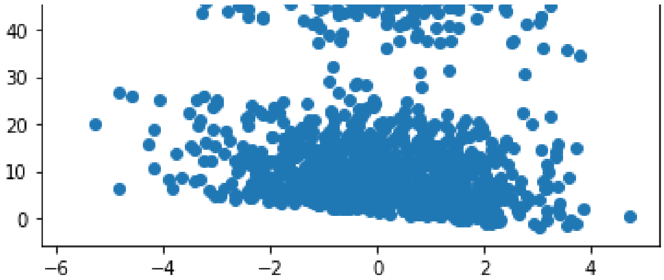


In [120]:

```
plt.scatter(residuals,predictions)

plt.show()
```





In [121]:

```
print(lm.coef_, lm.intercept_)
```

```
[-7.17686697e-07 -5.82600576e-01 -2.45889687e-02  2.97045812e+00
 -2.35260583e+00 -1.09786603e+00 -2.17154894e+00 -1.60262016e+00
 -4.74865031e+00 -4.99956239e+00  4.71027134e-02  1.21764063e-02
 -3.55432067e-04 -6.62759677e-03  2.44849274e-02 -3.60619790e-03
 -2.38043125e-03] -9.246391167714258
```

In [122]:

```
print("Intercept: ", lm.intercept_)
print("Coefficients:")
list(zip(X, lm.coef_))
```

```
Intercept:  -9.246391167714258
Coefficients:
```

Out[122]:

```
[('Income', -7.176866971400995e-07),
 ('Gender', -0.582600576431083),
 ('Contract', -0.024588968737316752),
 ('InternetService', 2.9704581221687603),
 ('Multiple', -2.352605828379221),
 ('OnlineSecurity', -1.0978660256712438),
 ('OnlineBackup', -2.1715489405226625),
 ('DeviceProtection', -1.6026201642220461),
 ('StreamingTV', -4.748650312242773),
 ('StreamingMovies', -4.999562393357259),
 ('MonthlyCharge', 0.04710271336936262),
 ('Bandwidth_GB_Year', 0.012176406345381993),
 ('Item2', -0.0003554320667647603),
 ('Item3', -0.006627596767938448),
 ('Item4', 0.024484927367230005),
 ('Item5', -0.0036061979040460193),
 ('Item7', -0.002380431245633076)]
```

We write the Multiple Linear Regression Equation as follows

Tenure = -9.2464 - (-7.1768e07 *Income)-(-0.5826* Gender)-(-0.0245 *Contract)- (2.9704* InternetService)-(-2.3526 *Mulitple)-(-1.0978* OnlineSecurity)-(-2.1715 *OnlineBackup)- (-1.6026* DeviceProtection)-(-4.7486 *StreamingTV)-(-4.7486* StreamingMovies)- (0.0471 *MonthlyCharge)-(0.0121* Bandwidth_GB_Year)-(-0.0003 *Item2)- (-0.0066* Item3)-(0.0244 *Item4)-(-0.0036* Item5)- (-0.0023 * Item7)

Comparison of Initial Backward Selection Model, Final Backward Selection Model, and Final Forward Selection Model

Our initial backward selection model had a higher R2 and lower MAE, MSE, and RMSE. Taking this consideration it also had some discernable patterns in the residual scatterplot, taking away from the integrity of the model, as the predictor variables might bet correlated. The points however did fall tighter on the prediction line in the reg plot when compared to our final backward selection model. The Final forward selection model was created to remedy these issues and gain greater insight. In our final forward model we can observe a higher R2 at .9966, when compared to the final backward model. This model also has a tighter fit on the reg plot prediction line than the previous models, and also has no discernable patterns within the residual scatterplot. The Final Forward Model is the most Accurate and Reliable Model

In linear regression, coefficients are the values that multiply the predictor values. The sign of each coefficient indicates the direction of the relationship between a predictor variable and the response variable. A positive sign indicates that as the predictor variable increases, the response variable also increases. This is significant because we can see what variables have the strongest correlation. In this case we can observe that InternetService, MonthlyCharge, and Bandwidth have the highest values. Our forward selection process revealed that Bandwidth_GB_Year had the most significant impact on Tenure, we can also see that pattern reveal itself in Correlation Matrix. We also see now that even though backward selection was successful for feature selection it did not necessarily give us the insight about the input variables, only the desired result, that is one drawback about utilizing only one selection method.

The aformentioned variables can be taken into consideration when creating future packages, or when determining where to allocate resources for the company to make a return on investment. If the Y value, Tenure, is responsive to these variables. We can increase Tenure by working with and around these variables.

A limitation of Multiple Linear Regression is the quality of the data and the uniqueness of it. We reduced our data with a correlation matrix but it is still hard to determine with certainty whether the independent variables are connected in some way. We are equiped with our understanding of the uniqueness of the data, and further investigation is required to determine if the data in correlated in ways that we did not quite frame for the question at hand. Another limitation is that the quality of the input variables determine the quality of the results. Our most significant variable is Bandwidth_GB_Year, other performance metrics are impactful but do not come close. The model relies heavily on this one metric and that takes away from the integrity of the model.

In [ ]:

```

```

Final Dataset

In [123]:

```
df.drop(["Tenure","Interaction","Customer_id","UID","Area","Job","City","County","TimeZone","State","Churn","CaseOrder","Zip","Lng","Lat","Population","Children","Age","CaseOrder","Zip","Lat","Lng","Population","Children","Age","Marital","Outage_sec_perweek","Email","Contacts","Yearly_equip_failure","Techie","Port_modem","Tablet","Phone","TechSupport","PaperlessBilling","PaymentMethod","Item1","Item6","Item8"],axis=1, inplace=True)
```

Final Dataset df

In [124]:

```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10000 entries, 0 to 9999
Data columns (total 17 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Income             10000 non-null  float64
 1   Gender             10000 non-null  int64  
 2   Contract           10000 non-null  int64  
 3   InternetService    10000 non-null  int64  
 4   Multiple           10000 non-null  int64  
 5   OnlineSecurity     10000 non-null  int64  
 6   OnlineBackup       10000 non-null  int64  
 7   DeviceProtection   10000 non-null  int64  
 8   StreamingTV        10000 non-null  int64  
 9   StreamingMovies    10000 non-null  int64  
 10  MonthlyCharge      10000 non-null  float64
 11  Bandwidth_GB_Year  10000 non-null  float64
 12  Item2              10000 non-null  int64  
 13  Item3              10000 non-null  int64  
 14  Item4              10000 non-null  int64  
 15  Item5              10000 non-null  int64  
 16  Item7              10000 non-null  int64  
dtypes: float64(3), int64(14)
memory usage: 1.3 MB
```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```

In [ ]:

```

```