In [27]:
```
import pandas as pd
telco_data = pd.read_csv('WA_Fn-UseC_-Telco-Customer-Churn.csv')
```

In [28]:
```
import warnings
warnings.filterwarnings("ignore")
import numpy as np
```

In [30]:
```
telco_data.columns
```

Out[30]:
```
Index(['customerID', 'gender', 'SeniorCitizen', 'Partner', 'Dependents',
       'tenure', 'PhoneService', 'MultipleLines', 'InternetService',
       'OnlineSecurity', 'OnlineBackup', 'DeviceProtection', 'TechSupport',
       'StreamingTV', 'StreamingMovies', 'Contract', 'PaperlessBilling',
       'PaymentMethod', 'MonthlyCharges', 'TotalCharges', 'Churn'],
      dtype='object')
```

In [31]:
```
telco_data.shape
```

Out[31]:
```
(7043, 21)
```

In [32]:
```
telco_data.head()
```

Out[32]:

	customerID	gender	SeniorCitizen	Partner	Dependents	tenure	PhoneService	MultipleLines
0	7590-VHVEG	Female	0	Yes	No	1	No	No phone service
1	5575-GNVDE	Male	0	No	No	34	Yes	No
2	3668-QPYBK	Male	0	No	No	2	Yes	No
3	7795-CFOCW	Male	0	No	No	45	No	No phone service
4	9237-HQITU	Female	0	No	No	2	Yes	No

5 rows × 21 columns

In [33]:
```
telco_data.dtypes
telco_data.drop(columns= 'customerID', inplace = True)
```

In [34]:
```
telco_data['TotalCharges'] = pd.to_numeric(telco_data['TotalCharges'], errors
= 'coerce')
#converting it to continuous as dtype was object
```

In [35]:
```
telco_continuous = telco_data.select_dtypes (include = ['int64','float64'])
telco_continuous.head()
telco_continuous.drop (columns = ['SeniorCitizen'],inplace = True)
```

In [36]:
```
cont_var = list (telco_continuous)
```

In [37]:
```
cont_var
```

Out[37]:
```
['tenure', 'MonthlyCharges', 'TotalCharges']
```

In [38]:
```
telco_continuous
```

Out[38]:

	tenure	MonthlyCharges	TotalCharges
0	1	29.85	29.85
1	34	56.95	1889.50
2	2	53.85	108.15
3	45	42.30	1840.75
4	2	70.70	151.65
5	8	99.65	820.50
6	22	89.10	1949.40
7	10	29.75	301.90
8	28	104.80	3046.05
9	62	56.15	3487.95
10	13	49.95	587.45
11	16	18.95	326.80
12	58	100.35	5681.10
13	49	103.70	5036.30
14	25	105.50	2686.05
15	69	113.25	7895.15
16	52	20.65	1022.95
17	71	106.70	7382.25
18	10	55.20	528.35
19	21	90.05	1862.90
20	1	39.65	39.65
21	12	19.80	202.25
22	1	20.15	20.15
23	58	59.90	3505.10
24	49	59.60	2970.30
25	30	55.30	1530.60
26	47	99.35	4749.15
27	1	30.20	30.20
28	72	90.25	6369.45
29	17	64.70	1093.10
...	...	...	...
7013	40	93.40	3756.40
7014	41	89.20	3645.75
7015	34	85.20	2874.45
7016	1	49.95	49.95

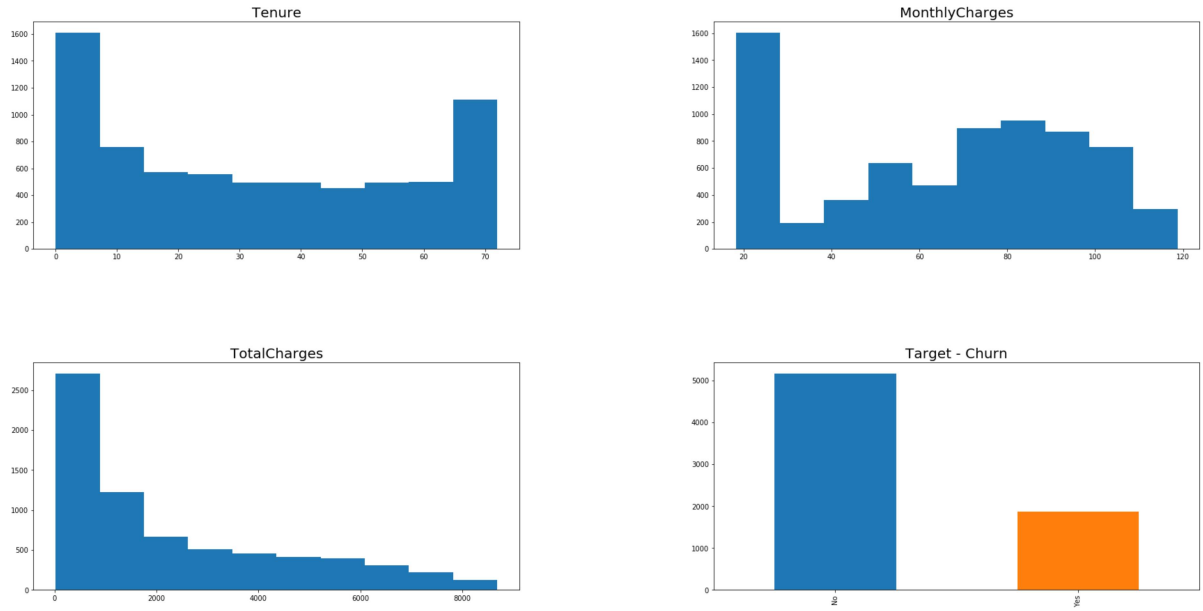
	tenure	MonthlyCharges	TotalCharges
7017	51	20.65	1020.75
7018	1	70.65	70.65
7019	39	20.15	826.00
7020	12	19.20	239.00
7021	12	59.80	727.80
7022	72	104.95	7544.30
7023	63	103.50	6479.40
7024	44	84.80	3626.35
7025	18	95.05	1679.40
7026	9	44.20	403.35
7027	13	73.35	931.55
7028	68	64.10	4326.25
7029	6	44.40	263.05
7030	2	20.05	39.25
7031	55	60.00	3316.10
7032	1	75.75	75.75
7033	38	69.50	2625.25
7034	67	102.95	6886.25
7035	19	78.70	1495.10
7036	12	60.65	743.30
7037	72	21.15	1419.40
7038	24	84.80	1990.50
7039	72	103.20	7362.90
7040	11	29.60	346.45
7041	4	74.40	306.60
7042	66	105.65	6844.50

7043 rows × 3 columns

2.1

In [39]:
```
import matplotlib.pyplot as plt
fig, ax = plt.subplots(2, 2, figsize=(30, 15))
plt.subplots_adjust(wspace=0.40,hspace=0.50)

ax[0,0].hist(telco_continuous['tenure'])
ax[0,1].hist(telco_continuous['MonthlyCharges'])
ax[1,0].hist(telco_continuous['TotalCharges'])

telco_data['Churn'].value_counts().plot(kind='bar', ax=ax[1,1])

ax[0,0].set_title('Tenure', fontsize = 20)
ax[0,1].set_title('MonthlyCharges', fontsize = 20)
ax[1,0].set_title('TotalCharges', fontsize = 20)
ax[1,1].set_title('Target - Churn', fontsize = 20)
```

Out[39]: Text(0.5, 1.0, 'Target - Churn')



2.2

In [40]:
```
cat_var = list(set(telco_data.columns)- set(telco_continuous.columns))
```

In [41]:
```
cat_var
```

Out[41]:
```
['StreamingTV',
 'TechSupport',
 'PaymentMethod',
 'PhoneService',
 'SeniorCitizen',
 'Contract',
 'Dependents',
 'OnlineBackup',
 'Partner',
 'MultipleLines',
 'InternetService',
 'Churn',
 'DeviceProtection',
 'PaperlessBilling',
 'OnlineSecurity',
 'StreamingMovies',
 'gender']
```

In [42]:
```
from sklearn.model_selection import train_test_split
cat_var.remove('Churn')
X_train, X_test, y_train, y_test = train_test_split (telco_data.loc[:, telco_d
ata.columns != 'Churn'],telco_data['Churn'], random_state = 0)
X_train = pd.concat((X_train[cat_var], X_train[cont_var]), axis=1)
```

In [43]:
```
from sklearn.compose import make_column_transformer
from sklearn.compose import ColumnTransformer

from sklearn.pipeline import make_pipeline
from sklearn.preprocessing import OneHotEncoder
from sklearn.impute import SimpleImputer


cat_pipe = ColumnTransformer([('imputer', SimpleImputer(strategy = 'median'),
cont_var) , ('ohe', OneHotEncoder(handle_unknown='ignore'), cat_var)], remaind
er='passthrough')
```

In [44]:
```
from sklearn.linear_model import LogisticRegression
from sklearn.model_selection import cross_val_score

logreg_model = make_pipeline(cat_pipe, LogisticRegression())
logreg_scores = cross_val_score(logreg_model, X_train, y_train, cv=10)
print('Logistic Regression: ', np.mean(logreg_scores))


from sklearn.svm import LinearSVC
linearSVC_model = make_pipeline(cat_pipe, LinearSVC())
linearSVC_scores = cross_val_score (linearSVC_model,X_train, y_train, cv=10)
print('Linear SVC: ', np.mean(linearSVC_scores))


from sklearn.neighbors.nearest_centroid import NearestCentroid
ncentroid_model = make_pipeline (cat_pipe,NearestCentroid())
ncentroid_scores = cross_val_score (ncentroid_model, X_train, y_train, cv=10)
print('N Centroid: ', np.mean(ncentroid_scores))
```

```
Logistic Regression:  0.8023444758109355
Linear SVC:  0.7317723821036433
N Centroid:  0.5238651567706784
```

The performance of Logistic Regression is better than Linear SVC and N Centroid

In [45]:
```
from sklearn.preprocessing import StandardScaler
scaler_pipe = ColumnTransformer([('scaling', StandardScaler(), cont_var)], rem
ainder='passthrough')
#cat_con_pipe = ColumnTransformer([('somename', StandardScaler(), ['tenure',
 'MonthlyCharges']),
                                  #('ohe', OneHotEncoder(handle_unknown='ignor
e'), cat_var)], remainder = 'passthrough')
cat_con_pipe = ColumnTransformer([('imputer', SimpleImputer(strategy = 'media
n'), np.arange (0,len(cont_var))) , ('ohe', OneHotEncoder(handle_unknown='igno
re'),  np.arange(len(cont_var),len(X_train.columns)))], remainder='passthroug
h')
```

In [46]:
```
logreg1_model = make_pipeline(scaler_pipe, cat_con_pipe, LogisticRegression())
logreg1_scores = cross_val_score(logreg1_model, X_train, y_train, cv=10)
print('Logistic Regression with Standard Scaling: ', np.mean(logreg1_scores))

linearSVC1_model = make_pipeline(scaler_pipe, cat_con_pipe,LinearSVC())
linearSVC1_scores = cross_val_score (linearSVC1_model,X_train, y_train, cv=10)
print('Linear SVC with Standard Scaling: ', np.mean(linearSVC1_scores))

ncentroid1_model = make_pipeline (scaler_pipe, cat_con_pipe, NearestCentroid
())
ncentroid1_scores = cross_val_score (ncentroid1_model, X_train, y_train, cv=10
)
print('N Centroid with Standard Scaling: ', np.mean(ncentroid1_scores))
```

```
Logistic Regression with Standard Scaling:  0.8025342291316185
Linear SVC with Standard Scaling:  0.8025370987470541
N Centroid with Standard Scaling:  0.7391182389170072
```

We see significant improvement in Linear SVC and N Centroid on Standard Scaling

2.3

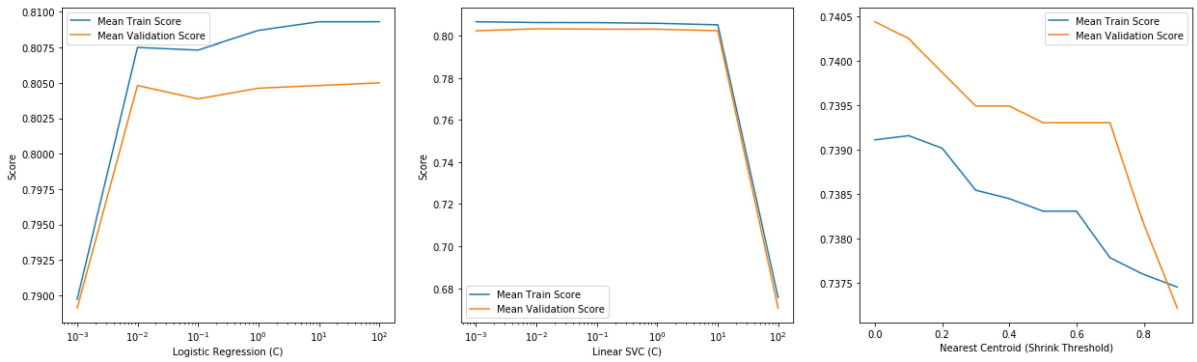
In [47]:
```
from sklearn.model_selection import GridSearchCV
from sklearn.pipeline import Pipeline

pipeline_logreg = Pipeline(steps=[('scaling',scaler_pipe), ('preprocess', cat_
con_pipe), ('logreg', LogisticRegression())])
pipeline_linearSVC = Pipeline(steps=[('scaling',scaler_pipe), ('preprocess', c
at_con_pipe), ('linearSVC', LinearSVC())])
pipeline_ncentroid = Pipeline(steps=[('scaling',scaler_pipe), ('preprocess', c
at_con_pipe), ('ncentroid', NearestCentroid())])

paragrid_logreg = {'logreg__C':np.logspace(-3,2,6)}
#'logreg__penalty': ['l1', 'l2']
paragrid_linearSVC = {'linearSVC__C': np.logspace(-3, 2, 6)}
#'linearSVC__gamma': np.logspace(-3, 2, 6) / X_train.shape[0]
paragrid_ncentroid = {'ncentroid__shrink_threshold': np.arange(0,1,0.1)}

gcv_logreg = GridSearchCV(pipeline_logreg, param_grid=paragrid_logreg, cv=5, r
eturn_train_score=True)
gcv_logreg.fit(X_train, y_train)
print("Logistic Regression best parameters with stratified kfold is {}".format
(gcv_logreg.best_params_))
print("Logistic Regression best score with stratified kfold is {}".format(gcv_
logreg.best_score_))


gcv_linearSVC = GridSearchCV(pipeline_linearSVC, param_grid=paragrid_linearSVC
, cv=5, return_train_score=True)
gcv_linearSVC.fit(X_train, y_train)
print("Linear SVC best parameters with stratified kfold is {}".format(gcv_line
arSVC.best_params_))
print("Linear SVC best score with stratified kfold is {}".format(gcv_linearSVC
.best_score_))


gcv_ncentroid = GridSearchCV(pipeline_ncentroid, param_grid=paragrid_ncentroid
, cv=5, return_train_score=True)
gcv_ncentroid.fit(X_train, y_train)
print("Nearest Centroid best parameters with stratified kfold is {}".format(gc
v_ncentroid.best_params_))
print("Nearest Centroid best score with stratified kfold is {}".format(gcv_nce
ntroid.best_score_))
```

```
Logistic Regression best parameters with stratified kfold is {'logreg__C': 10
0.0}
Logistic Regression best score with stratified kfold is 0.8049981067777358
Linear SVC best parameters with stratified kfold is {'linearSVC__C': 0.01}
Linear SVC best score with stratified kfold is 0.8032942067398713
Nearest Centroid best parameters with stratified kfold is {'ncentroid__shrink
_threshold': 0.0}
Nearest Centroid best score with stratified kfold is 0.7404392275653162
```

There is a very slight improvement when compared to the earlier models on using gridsearch

In [48]:
```
fig, ax = plt.subplots(1,3,figsize = (21,6))
logreg_result = pd.DataFrame(gcv_logreg.cv_results_)
ax[0].plot(logreg_result['param_logreg__C'], logreg_result['mean_train_score'
], label = 'Mean Train Score')
ax[0].plot(logreg_result['param_logreg__C'], logreg_result['mean_test_score'],
label = 'Mean Validation Score')
ax[0].set_xscale('log')
ax[0].legend(loc="best")
ax[0].set_xlabel('Logistic Regression (C)')
ax[0].set_ylabel('Score')

linearSVC_result = pd.DataFrame(gcv_linearSVC.cv_results_)
ax[1].plot(linearSVC_result['param_linearSVC__C'], linearSVC_result['mean_trai
n_score'], label = 'Mean Train Score')
ax[1].plot(linearSVC_result['param_linearSVC__C'], linearSVC_result['mean_test
_score'], label = 'Mean Validation Score')
ax[1].set_xscale('log')
ax[1].legend(loc="best")

ax[1].set_xlabel('Linear SVC (C)')
ax[1].set_ylabel('Score')

ncentroid_result = pd.DataFrame(gcv_ncentroid.cv_results_)
ax[2].plot(ncentroid_result['param_ncentroid__shrink_threshold'], ncentroid_re
sult['mean_train_score'], label = 'Mean Train Score')
ax[2].plot(ncentroid_result['param_ncentroid__shrink_threshold'], ncentroid_re
sult['mean_test_score'], label = 'Mean Validation Score')
ax[2].legend(loc="best")

ax[2].set_xlabel('Nearest Centroid (Shrink Threshold)')
ax[1].set_ylabel('Score')
```

Out[48]: Text(0, 0.5, 'Score')



2.4

In [53]:
```
from sklearn.model_selection import KFold
kfold = KFold(n_splits=5, shuffle = True)


paragrid_logreg = {'logreg__C':np.logspace(-3,2,6)}
#'logreg__penalty': ['l1', 'l2']
paragrid_linearSVC = {'linearSVC__C': np.logspace(-3, 2, 6)}
#'linearSVC__gamma': np.logspace(-3, 2, 6) / X_train.shape[0]
paragrid_ncentroid = {'ncentroid__shrink_threshold': np.arange(0,1,0.1)}

gcv_logreg_kfold = GridSearchCV(pipeline_logreg, param_grid=paragrid_logreg, c
v=kfold, return_train_score=True)
gcv_logreg_kfold.fit(X_train, y_train)
print("Logistic Regression best parameter with kfold is {}".format(gcv_logreg_
kfold.best_params_))
print("Logistic Regression best score with kfold is {}".format(gcv_logreg_kfol
d.best_score_))


gcv_linearSVC_kfold = GridSearchCV(pipeline_linearSVC, param_grid=paragrid_lin
earSVC, cv=kfold, return_train_score=True)
gcv_linearSVC_kfold.fit(X_train, y_train)
print("Linear SVC best parameter with kfold is {}".format(gcv_linearSVC_kfold.
best_params_))
print("Linear SVC best score with kfold is {}".format(gcv_linearSVC_kfold.best
_score_))


gcv_ncentroid_kfold = GridSearchCV(pipeline_ncentroid, param_grid=paragrid_nce
ntroid, cv=kfold, return_train_score=True)
gcv_ncentroid_kfold.fit(X_train, y_train)
print("Nearest Centroid best parameter with kfold is {}".format(gcv_ncentroid_
kfold.best_params_))
print("Nearest Centroid best score with kfold is {}".format(gcv_ncentroid_kfol
d.best_score_))
```

```
Logistic Regression best parameter with kfold is {'logreg__C': 10.0}
Logistic Regression best score with kfold is 0.8068913290420295
Linear SVC best parameter with kfold is {'linearSVC__C': 0.1}
Linear SVC best score with kfold is 0.8059447179098826
Nearest Centroid best parameter with kfold is {'ncentroid__shrink_threshold':
0.30000000000000004}
Nearest Centroid best score with kfold is 0.7387353275274517
```

- C parameter for logistic regression is constant from 100 to 10
- C parameter for linear SVC changed from 0.01 to 0.001
- C parameter for N Centroid changes from 0.0 to 0.4

In [51]:
```
kfold = KFold(n_splits=5, shuffle = True,random_state = 1)

gcv_logreg_kfold_seed= GridSearchCV(pipeline_logreg, param_grid=paragrid_logre
g, cv=kfold, return_train_score=True)
gcv_logreg_kfold_seed.fit(X_train, y_train)
print("Logistic Regression best parameter with shuffle and seed is {}".format(
gcv_logreg_kfold_seed.best_params_))
print("Logistic Regression best score with shuffle and seed is {}".format(gcv_
logreg_kfold_seed.best_score_))


gcv_linearSVC_kfold_seed = GridSearchCV(pipeline_linearSVC, param_grid=paragri
d_linearSVC, cv=kfold, return_train_score=True)
gcv_linearSVC_kfold_seed.fit(X_train, y_train)
print("Linear SVC best parameter with shuffle and seed is {}".format(gcv_linea
rSVC_kfold_seed.best_params_))
print("Linear SVC best score with shuffle and seed is {}".format(gcv_linearSVC
_kfold_seed.best_score_))


gcv_ncentroid_kfold_seed = GridSearchCV(pipeline_ncentroid, param_grid=paragri
d_ncentroid, cv=kfold, return_train_score=True)
gcv_ncentroid_kfold_seed.fit(X_train, y_train)
print("Nearest Centroid best parameter with shuffle and seed is {}".format(gcv
_ncentroid_kfold_seed.best_params_))
print("Nearest Centroid best score with shuffle and seed is {}".format(gcv_nce
ntroid_kfold_seed.best_score_))
```

```
Logistic Regression best parameter with shuffle and seed is {'logreg__C': 0.0
1}
Logistic Regression best score with shuffle and seed is 0.8065126845891708
Linear SVC best parameter with shuffle and seed is {'linearSVC__C': 0.001}
Linear SVC best score with shuffle and seed is 0.8055660734570238
Nearest Centroid best parameter with shuffle and seed is {'ncentroid__shrink_
threshold': 0.4}
Nearest Centroid best score with shuffle and seed is 0.7391139719803105
```

The below parameters change in comparison to 2.3 Stratified K-fold

- C parameter for logistic regression changed from 100 to 0.01
- C parameter for linear SVC changed from 0.01 to 0.001
- C parameter for N Centroid changed from 0 to 0.4

In [54]:
```
X1_train, X1_test, y1_train, y1_test = train_test_split (telco_data.loc[:, tel
co_data.columns != 'Churn'],telco_data['Churn'], random_state = 10)
X1_train = pd.concat((X1_train[cat_var], X1_train[cont_var]), axis=1)


gcv_logreg_kfold_tt = GridSearchCV(pipeline_logreg, param_grid=paragrid_logreg
, cv=kfold, return_train_score=True)
gcv_logreg_kfold_tt.fit(X1_train, y1_train)
print("Logistic Regression best parameter with kfold and train test seed chang
e is {}".format(gcv_logreg_kfold_tt.best_params_))
print("Logistic Regression best score with kfold and train test seed change is
{}".format(gcv_logreg_kfold_tt.best_score_))


gcv_linearSVC_kfold_tt = GridSearchCV(pipeline_linearSVC, param_grid=paragrid_
linearSVC, cv=kfold, return_train_score=True)
gcv_linearSVC_kfold_tt.fit(X1_train, y1_train)
print("Linear SVC best parameter with kfold and train test seed change is {}".
format(gcv_linearSVC_kfold_tt.best_params_))
print("Linear SVC best score with kfold and train test seed change is {}".form
at(gcv_linearSVC_kfold_tt.best_score_))


gcv_ncentroid_kfold_tt = GridSearchCV(pipeline_ncentroid, param_grid=paragrid_
ncentroid, cv=kfold, return_train_score=True)
gcv_ncentroid_kfold_tt.fit(X1_train, y1_train)
print("Nearest Centroid best parameter with kfold and train test seed change i
s {}".format(gcv_ncentroid_kfold_tt.best_params_))
print("Nearest Centroid best score with kfold and train test seed change is {}
".format(gcv_ncentroid_kfold_tt.best_score_))
```

```
Logistic Regression best parameter with kfold and train test seed change is
{'logreg__C': 0.01}
Logistic Regression best score with kfold and train test seed change is 0.805
1874290041651
Linear SVC best parameter with kfold and train test seed change is {'linearSV
C__C': 0.1}
Linear SVC best score with kfold and train test seed change is 0.804240817872
0182
Nearest Centroid best parameter with kfold and train test seed change is {'nc
entroid__shrink_threshold': 0.0}
Nearest Centroid best score with kfold and train test seed change is 0.738356
683074593
```

The below parameters change in comparison to 2.3 Stratified K-fold

- C parameter for logistic regression changed from 100 to 0.01
- C parameter for linear SVC changed from 0.01 to 0.001
- C parameter for N Centroid is constant from at 0.0

2.5

Logistic Regression best score with kfold --> C = 1 and score = 0.8068

Linear SVC best score also with kfold --> c = 10 and score = 0.8059

In [57]:
```
coeff_logreg = gcv_logreg_kfold.best_estimator_.named_steps['logreg'].coef_[0]
coeff_linearSVC = gcv_linearSVC_kfold.best_estimator_.named_steps['linearSVC']
.coef_[0]
```

In [77]:
```
len(coeff_logreg)
```

Out[77]: 46

In [83]:
```
fig, ax = plt.subplots(1,2, figsize=(16,6))
plt.subplots_adjust(wspace=0.2,hspace=0.60)

ax[0].plot(coeff_logreg, 'o', label = "C = 10.0", color = 'red')
ax[0].set_title ('Co-efficients of Best Performing Logistic Regression (k-fol
d)')
ax[0].set_ylabel ('Co-efficient Value')
ax[0].legend()
ax[0].set_xlabel ('Feature Position')



ax[1].plot(coeff_linearSVC, 'o', label = "C = 0.1")
ax[1].set_title ('Co-efficients of Best Performing Linear SVC (k-fold)')
ax[1].set_ylabel ('Co-efficient Value')
ax[1].legend()
ax[1].set_xlabel ('Feature Position')
```

Out[83]: Text(0.5, 0, 'Feature Position')