In [1]:
```python
import pandas as pd
from ast import literal_eval
import seaborn as sns
import matplotlib.pyplot as plt
%matplotlib inline
import numpy as np
```

In [2]:
```python
import nltk
import re
nltk.download('stopwords')
nltk.download('punkt')
nltk.download('wordnet')
from nltk.corpus import stopwords
from nltk.stem import WordNetLemmatizer
from sklearn.feature_extraction.text import TfidfVectorizer, CountVectorizer
from sklearn.model_selection import train_test_split
from nltk.stem import PorterStemmer
```

```
[nltk_data] Downloading package stopwords to
[nltk_data]     C:\Users\rezar\AppData\Roaming\nltk_data...
[nltk_data]   Package stopwords is already up-to-date!
[nltk_data] Downloading package punkt to
[nltk_data]     C:\Users\rezar\AppData\Roaming\nltk_data...
[nltk_data]   Package punkt is already up-to-date!
[nltk_data] Downloading package wordnet to
[nltk_data]     C:\Users\rezar\AppData\Roaming\nltk_data...
[nltk_data]   Package wordnet is already up-to-date!
```

Load Data

In [68]:
```python
path = 'dataset/' #change to your data location
# load downloaded data
df_convos = pd.read_csv(path+'/conversations.csv')
df_speakers = pd.read_csv(path+'/speakers.csv')
df_utts = pd.read_csv(path+'/utterances.csv')
df_cases = pd.read_json(path_or_buf=path+'/cases.jsonl', lines=True)
df_cases = df_cases[(df_cases['year'] >= 2011) & (df_cases['year'] <= 2018) & (df_cases['win_side'].isin([0,1]))]
```

In [69]:
```python
# count number win/lose cases
df_cases['win_side'].value_counts()
```

Out[69]:
```
1.0    400
0.0    201
Name: win_side, dtype: int64
```

In [70]:
```python
# combine text from all utterances in a conversation back into one string based on the conversation_id, coount how many utterances
utt_per_conv = df_utts.groupby('conversation_id')['text'].apply(lambda x: ' '.join(x)).reset_index()
utt_per_conv['num_utterances'] = df_utts.groupby('conversation_id')['text'].count().reset_index()['text']

# add the combined text to the conversations dataframe, merge on conversation_id in utt_per_conv and id in df_convo
df_convos_utt = df_convos.merge(utt_per_conv, left_on='id', right_on='conversation_id', how='left')
```

In [71]:
```python
# combine text from all conversation in a cases into one string based on the meta.case_id
conv_per_case = df_convos_utt.groupby('meta.case_id')['text'].apply(lambda x: ' '.join(x)).reset_index()
conv_per_case['num_conversations'] = df_convos_utt.groupby('meta.case_id')['text'].count().reset_index()['text']
conv_per_case['num_utterances'] = df_convos_utt.groupby('meta.case_id')['num_utterances'].sum().reset_index()['num_utterances']

# add the combined text case dataframe, merge on meta.case_id and id
df_cases_convo = df_cases.merge(conv_per_case, left_on='id', right_on='meta.case_id', how='left')
df_cases_convo.head(1)
```

Out[71]:

	id	year	citation	title	petitioner	respondent	docket_no	court	decided_date	url	...	win_side_detail
0	2011_11-1179	2011	567 US _	American Tradition Partnership, Inc. v. Bullock	American Tradition Partnership, Inc.	Steve Bullock, Attorney General of Montana, et...	11-1179	Roberts Court	Jun 25, 2012	https://www.oyez.org/cases/2011/11-1179	...	3.0

1 rows × 25 columns

In [72]:
```python
df_cases_convo.dropna(subset=['text'], inplace=True)
df_cases_convo.shape[0]
```

Out[72]: 521

In [73]:
```python
# transform to pd.to_datetime
df_cases_convo.decided_date = pd.to_datetime(df_cases_convo.decided_date)
```

Data Preprocessing

In [74]:
```python
# Cleaning the text
def preprocess_text(text):
    text = text.lower() # Lowercase the text
    text = re.sub('[^a-z]+', ' ', text)  # Remove special characters and numbers
    text = re.sub(r'\b\w{1,3}\b', '', text) # Remove words with length less than 3
    words = nltk.word_tokenize(text) # Tokenize the text
    stop_words = set(stopwords.words('english')) # Remove stopwords
    words = [word for word in words if word not in stop_words]
    #lemmatizer = WordNetLemmatizer() # Lemmatize the words comment because slow
    #words = [lemmatizer.lemmatize(word) for word in words]
    stemmer = PorterStemmer() # Stem the words
    words = [stemmer.stem(word) for word in words]
    text = ' '.join(words) # Reconstruct the text

    return text
```

In [75]:
```python
df_cases_convo.loc[:,'text'] = df_cases_convo.loc[:,'text'].apply(preprocess_text) #apply preprocess
df_cases_convo.to_csv('df_cases_clean.csv', index=False)
```

In [76]:
```python
text = pd.read_csv('df_cases_clean.csv')
text.head(1)
```

Out[76]:

	id	year	citation	title	petitioner	respondent	docket_no	court	decided_date	url	...	win_side_detail	scdb
0	2011_11-182	2011	567 US _	Arizona v. United States	Arizona et al.	United States	11-182	Roberts Court	2012-06-25	https://www.oyez.org/cases/2011/11-182	...	7.0	2

1 rows × 25 columns

In [105...
```python
df_cases_convo.columns
```

Out[105]:
```
Index(['id', 'year', 'citation', 'title', 'petitioner', 'respondent',
       'docket_no', 'court', 'decided_date', 'url', 'transcripts',
       'adv_sides_inferred', 'known_respondent_adv', 'advocates', 'win_side',
       'win_side_detail', 'scdb_docket_id', 'votes', 'votes_detail',
       'is_eq_divided', 'votes_side', 'meta.case_id', 'text',
       'num_conversations', 'num_utterances', 'start_date', 'develop_time'],
      dtype='object')
```

In [77]:
```python
# preprocess develop time
df_cases_convo.loc[:, 'start_date'] = df_cases_convo['transcripts'].apply(lambda x : re.findall(r'[A-Z][a-z]+ \d{2}, \d{4}', x[0][
df_cases_convo.start_date = pd.to_datetime(df_cases_convo.start_date)
df_cases_convo.loc[:, 'develop_time'] = df_cases_convo.loc[:, 'decided_date'] - df_cases_convo.loc[:, 'start_date']
```

In [78]:
```python
# get party of the judges
def check_party_pc(x):
    rep_judge = ['j__clarence_thomas', 'j__anthony_m_kennedy', 'j__antonin_scalia', 'j__john_g_roberts_jr', 'j__samuel_a_alito_jr'
             'j__john_paul_stevens', 'j__david_h_souter', 'j__william_h_rehnquist', 'j__neil_gorsuch', 'j__brett_m_kavanaugh']
    dem_judge = ['j__ruth_bader_ginsburg', 'j__stephen_g_breyer','j__sonia_sotomayor','j__elena_kagan']

    rep_ct = 0

    for judge in x:
        if judge in rep_judge:
            rep_ct += 1

    return rep_ct/len(x)
```

In [79]:
```python
# get rep_judge yes
def check_rep_j_y_pc(x):
    rep_judge = ['j__clarence_thomas', 'j__anthony_m_kennedy', 'j__antonin_scalia', 'j__john_g_roberts_jr', 'j__samuel_a_alito_jr'
             'j__john_paul_stevens', 'j__david_h_souter', 'j__william_h_rehnquist', 'j__neil_gorsuch', 'j__brett_m_kavanaugh']
    dem_judge = ['j__ruth_bader_ginsburg', 'j__stephen_g_breyer','j__sonia_sotomayor','j__elena_kagan']
```

```python
    rep_y_ct = 0

    for judge in x:
        if judge in rep_judge:
            if x[judge] > 0:
                rep_y_ct += 1

    return rep_y_ct/len(x)
```

In [80]:
```python
# get dem_judge yes
def check_dem_j_y_pc(x):
    rep_judge = ['j__clarence_thomas', 'j__anthony_m_kennedy', 'j__antonin_scalia', 'j__john_g_roberts_jr', 'j__samuel_a_alito_jr'
             'j__john_paul_stevens', 'j__david_h_souter', 'j__william_h_rehnquist', 'j__neil_gorsuch', 'j__brett_m_kavanaugh']
    dem_judge = ['j__ruth_bader_ginsburg', 'j__stephen_g_breyer','j__sonia_sotomayor','j__elena_kagan']

    dem_y_ct = 0

    for judge in x:
        if judge in dem_judge:
            if x[judge] > 0:
                dem_y_ct += 1

    return dem_y_ct/len(x)
```

In [81]:
```python
def check_party(x):
    if x > 2009:
        return 0
    else:
        return 1
```

In [82]:
```python
# get M-F percentage in judges
def check_FM_jpc(x):
    male_judge = ['j__clarence_thomas',
                  'j__anthony_m_kennedy',
                  'j__antonin_scalia',
                  'j__john_g_roberts_jr',
                  'j__samuel_a_alito_jr',
                  'j__john_paul_stevens',
                  'j__david_h_souter',
                  'j__william_h_rehnquist',
                  'j__neil_gorsuch',
                  'j__brett_m_kavanaugh',
                  'j__stephen_g_breyer']
    female_judge = ['j__ruth_bader_ginsburg',
                    'j__sonia_sotomayor',
                    'j__elena_kagan']
    male_ct = 0
    for judge in x:
        if judge in male_judge:
            male_ct += 1

    return male_ct/len(x)
```

In [83]:
```python
# get rep_judge yes
def check_M_j_y_pc(x):
    male_judge = ['j__clarence_thomas',
                  'j__anthony_m_kennedy',
                  'j__antonin_scalia',
                  'j__john_g_roberts_jr',
                  'j__samuel_a_alito_jr',
                  'j__john_paul_stevens',
                  'j__david_h_souter',
                  'j__william_h_rehnquist',
                  'j__neil_gorsuch',
                  'j__brett_m_kavanaugh',
                  'j__stephen_g_breyer']
    female_judge = ['j__ruth_bader_ginsburg',
                    'j__sonia_sotomayor',
                    'j__elena_kagan']
    male_y_ct = 0
    for judge in x:
        if judge in male_judge:
            if x[judge] > 0:
                male_y_ct += 1
    return male_y_ct/len(x)
```

In [84]:
```python
# get rep_judge yes
def check_F_j_y_pc(x):
    male_judge = ['j__clarence_thomas',
                  'j__anthony_m_kennedy',
```

```
                 'j__antonin_scalia',
                 'j__john_g_roberts_jr',
                 'j__samuel_a_alito_jr',
                 'j__john_paul_stevens',
                 'j__david_h_souter',
                 'j__william_h_rehnquist',
                 'j__neil_gorsuch',
                 'j__brett_m_kavanaugh',
                 'j__stephen_g_breyer']
    female_judge = ['j__ruth_bader_ginsburg',
                   'j__sonia_sotomayor',
                   'j__elena_kagan']
    female_y_ct = 0
    for judge in x:
        if judge in female_judge:
            if x[judge] > 0:
                female_y_ct += 1
    return female_y_ct/len(x)
```

In [85]:

```
# get first name of speakers
df_test = df_cases_convo.loc[:, ['advocates']]

def get_side1_fstname(x):
    return list(x.keys())[0].split()[0]

def get_side0_fstname(x):
    try:
        return list(x.keys())[-1].split()[0]
    except:
        return list(x.keys())[-2].split()[0]

df_test.loc[:, 'side1_fstname'] = df_test['advocates'].apply(get_side1_fstname)
df_test.loc[:, 'side0_fstname'] = df_test['advocates'].apply(get_side0_fstname)

# read gender dataset
df_gender = pd.read_csv('dataset/name_gender_dataset.csv')
idx = df_gender.groupby(['Name'])['Probability'].idxmax()
df_gender = df_gender.loc[idx]

# join the gender dataset to predict gender of speakers
df_test = pd.merge(df_test, df_gender, how='left', left_on = 'side1_fstname', right_on = 'Name')
df_test = pd.merge(df_test, df_gender, how='left', left_on = 'side0_fstname', right_on = 'Name')
```

In [113…

```
# only numbers can apply to Random Forest Model
df_rf = pd.DataFrame()
df_rf.loc[:, 'text_len'] = df_cases_convo['text'].apply(lambda x : len(x))
df_rf.loc[:, 'num_utterances'] = df_cases_convo['num_utterances']
df_rf.loc[:, 'win_side'] = df_cases_convo['win_side']
df_rf.loc[:, 'develop_time'] = df_cases_convo['develop_time'].apply(lambda x : x.days)
df_rf.loc[:, 'rep_jpc'] = df_cases_convo['votes_side'].apply(check_party_pc)
df_rf.loc[:, 'dem_jpc'] = 1 - df_rf.loc[:, 'rep_jpc']
df_rf.loc[:, 'rep_j_y_pc'] = df_cases_convo['votes_side'].apply(check_rep_j_y_pc)
df_rf.loc[:, 'dem_j_y_pc'] = df_cases_convo['votes_side'].apply(check_dem_j_y_pc)
df_rf.loc[:, 'party'] = df_cases_convo['year'].apply(check_party) # 1:  rep, 0: dem
df_rf.loc[:, 'male_jpc'] = df_cases_convo['votes_side'].apply(check_FM_jpc)
df_rf.loc[:, 'female_jpc'] = 1 - df_rf.loc[:, 'male_jpc']
df_rf.loc[:, 'male_y_jpc'] = df_cases_convo['votes_side'].apply(check_M_j_y_pc)
df_rf.loc[:, 'female_y_jpc'] = df_cases_convo['votes_side'].apply(check_F_j_y_pc)
df_rf.loc[:, 'text'] = df_cases_convo['text']
df_rf.loc[:, 'num_conversations'] = df_cases_convo['num_conversations']

# reset the index
df_rf = df_rf.reset_index(drop=True)
df_rf.loc[:, 'side1_gender'] = df_test['Gender_x'].apply(lambda x: 0 if(x == 'F') else 1)
df_rf.loc[:, 'side0_gender'] = df_test['Gender_y'].apply(lambda x: 0 if(x == 'F') else 1)
```

In [88]:

```
df_rf.to_csv('dataset/df_rf.csv', index=False)
```

In [3]:

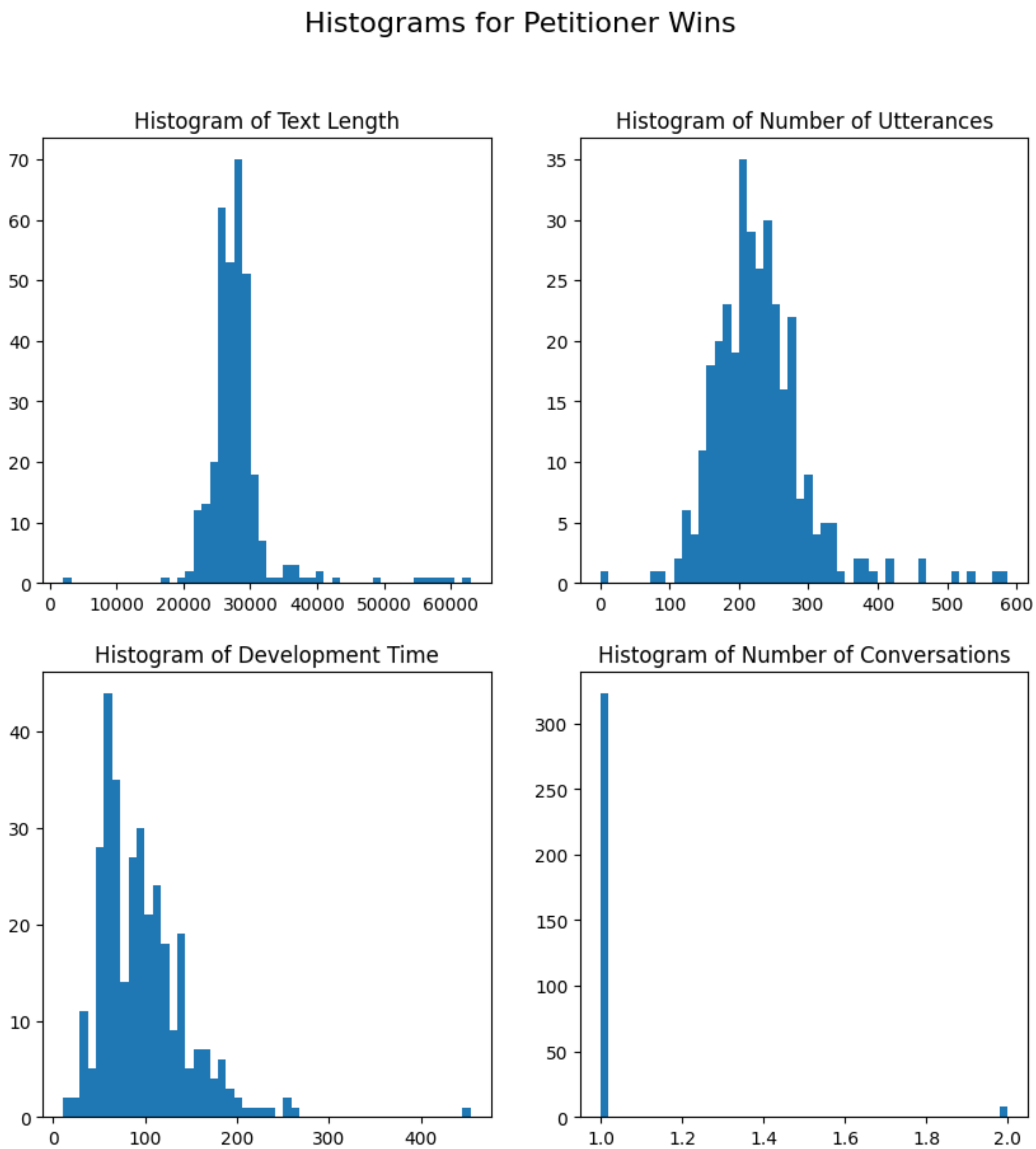
```
df_rf = pd.read_csv('dataset/df_rf.csv')
```

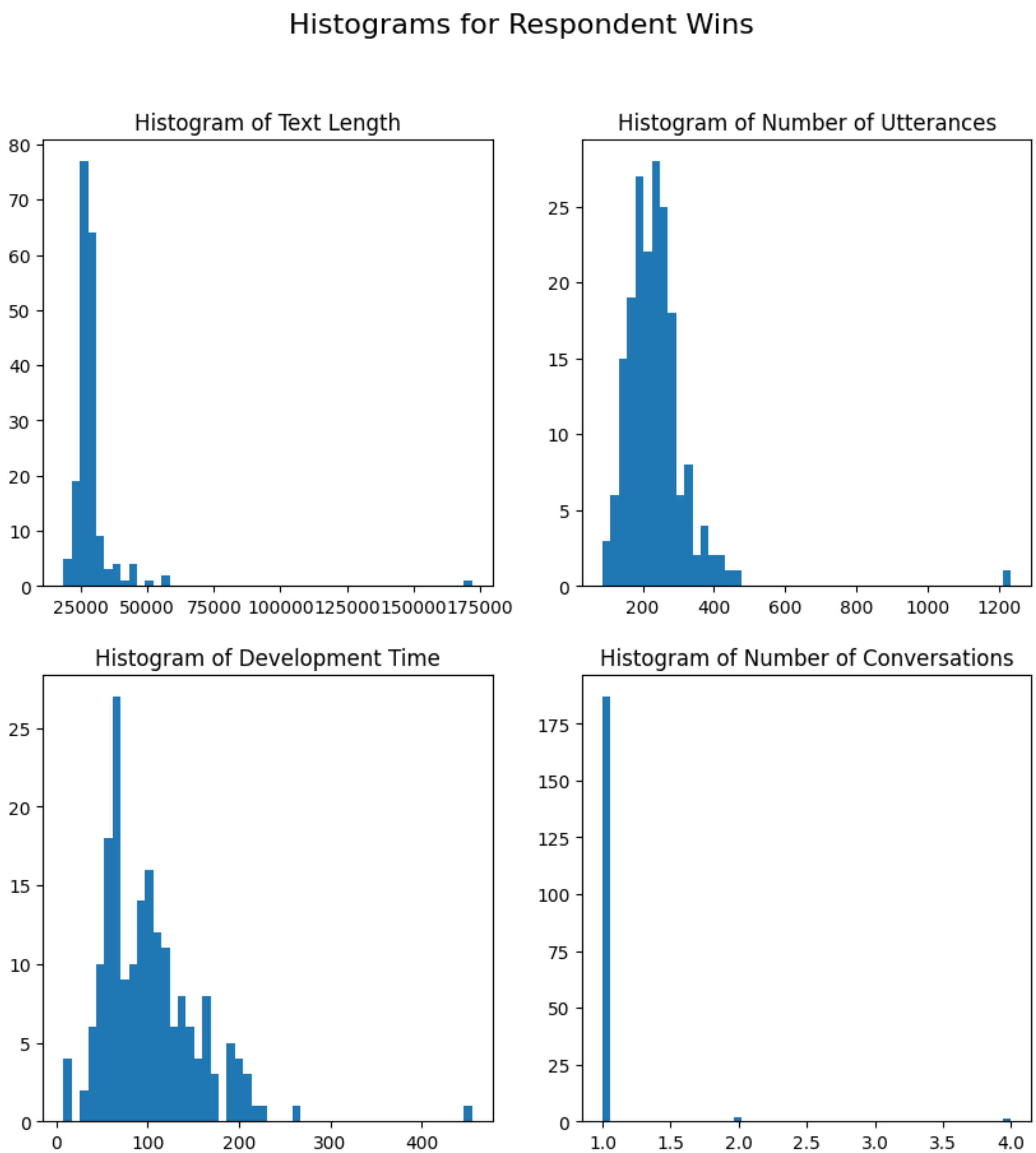
Additional Graphs for Checkpoint 1

In [4]:

```
# Histogram of text length, number of utterances, and development time, and number of conversations for win_side = 1
fig, ax = plt.subplots(2, 2, figsize=(10, 10))
ax[0, 0].hist(df_rf[df_rf['win_side'] == 1]['text_len'], bins=50)
ax[0, 0].set_title('Histogram of Text Length')
ax[0, 1].hist(df_rf[df_rf['win_side'] == 1]['num_utterances'], bins=50)
ax[0, 1].set_title('Histogram of Number of Utterances')
ax[1, 0].hist(df_rf[df_rf['win_side'] == 1]['develop_time'], bins=50)
```

```
ax[1, 0].set_title('Histogram of Development Time')
ax[1, 1].hist(df_rf[df_rf['win_side'] == 1]['num_conversations'], bins=50)
ax[1, 1].set_title('Histogram of Number of Conversations')
fig.suptitle('Histograms for Petitioner Wins', fontsize=16)
plt.savefig('histogram1.png')

# Histogram of text length, number of utterances, and development time, and number of conversations for win_side = 0
fig, ax = plt.subplots(2, 2, figsize=(10, 10))
ax[0, 0].hist(df_rf[df_rf['win_side'] == 0]['text_len'], bins=50)
ax[0, 0].set_title('Histogram of Text Length')
ax[0, 1].hist(df_rf[df_rf['win_side'] == 0]['num_utterances'], bins=50)
ax[0, 1].set_title('Histogram of Number of Utterances')
ax[1, 0].hist(df_rf[df_rf['win_side'] == 0]['develop_time'], bins=50)
ax[1, 0].set_title('Histogram of Development Time')
ax[1, 1].hist(df_rf[df_rf['win_side'] == 0]['num_conversations'], bins=50)
ax[1, 1].set_title('Histogram of Number of Conversations')
fig.suptitle('Histograms for Respondent Wins', fontsize=16)
plt.savefig('histogram0.png')
```





Baseline

In [5]:
```
# Calculate The Baseline for Accuracy, Precision, Recall, F1
accuracy = df_rf['win_side'].value_counts()[1]/df_rf['win_side'].shape[0]
print('Accuracy: ', accuracy)
```

```
Accuracy:  0.6353166986564299
```

Model Selection and Vectorize

In [45]:
```
from sklearn.linear_model import LogisticRegression, Perceptron, SGDClassifier
from sklearn.neighbors import KNeighborsClassifier
from sklearn.ensemble import RandomForestClassifier
from sklearn.naive_bayes import MultinomialNB
from sklearn.svm import LinearSVC
from sklearn.metrics import accuracy_score, confusion_matrix, classification_report, \
    f1_score, make_scorer, precision_score, recall_score, ConfusionMatrixDisplay, roc_auc_score, roc_curve, auc


def Classifier(X_train, X_test, y_train, y_test):

    # Train and evaluate the classifiers
    classifiers = {
        "Logistic Regression": LogisticRegression(max_iter=1000),
```

```
        "Naive Bayes": MultinomialNB(),
        "Linear SVC": LinearSVC(),
        "Random Forest": RandomForestClassifier(),
        "Perceptron": Perceptron(),
        "KNN": KNeighborsClassifier(n_neighbors=7)

    }

    results = []

    for classifier_name, classifier in classifiers.items():

        # Train the classifier
        classifier.fit(X_train, y_train)

        # Make predictions on the test set
        y_pred = classifier.predict(X_test)

        # Add the scores to the results dictionary
        results.append({
            'classifier': classifier_name,
            'accuracy': accuracy_score(y_test, y_pred),
            'f1': f1_score(y_test, y_pred),
            'precision': precision_score(y_test, y_pred),
            'recall': recall_score(y_test, y_pred),
            'True Negative Rate': confusion_matrix(y_test, y_pred)[0][0]/(confusion_matrix(y_test, y_pred)[0][0]+confusion_matrix(
            'True Positive Rate': confusion_matrix(y_test, y_pred)[1][1]/(confusion_matrix(y_test, y_pred)[1][1]+confusion_matrix(
            'auc': roc_auc_score(y_test, y_pred)
        })

        # Make a confusion matrix
        print(f"Confusion Matrix for {classifier_name}:")

        if classifier_name == "Logistic Regression":
            print("Coefficients: \n", classifier.coef_)

        cm = confusion_matrix(y_test, y_pred, labels=y_test.unique())
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=y_test.unique())
        fig, ax = plt.subplots(figsize=(3, 3))
        ax.set_title(f"CM {classifier_name}:")
        disp.plot(ax=ax)
        plt.show()
    return pd.DataFrame(results)
```

In [5]:

```
def Vectorize(vectorizer, X, y):
    X = vectorizer.fit_transform(X)
    y = y
    return X, y
```

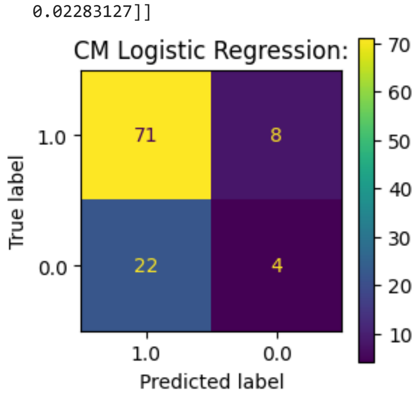
Using 'Text' as the feature

Text as Features and using TF-IDF Vectorizer

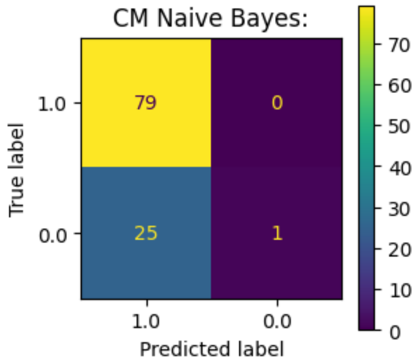
In [10]:

```
# Vectorize the text using TF-IDF
vectorizer = TfidfVectorizer(min_df=5, max_df=0.7)
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

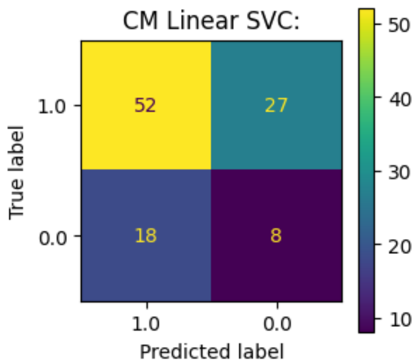
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.11731986  0.04298986 -0.00358675 ... -0.0470672   0.00655914
   0.02283127]]
```



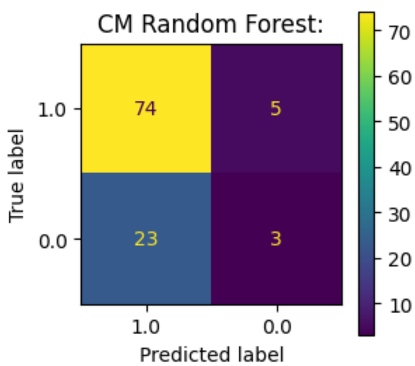

```
Confusion Matrix for Naive Bayes:
```



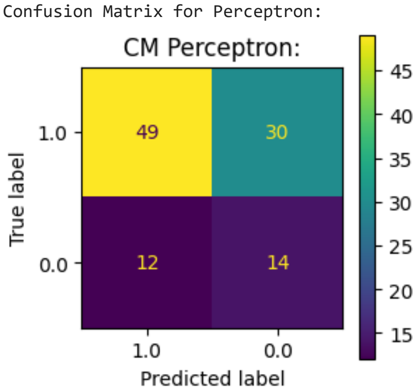
Confusion Matrix for Linear SVC:



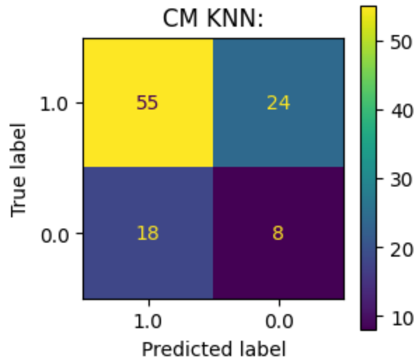
Confusion Matrix for Random Forest:



Confusion Matrix for Perceptron:



Confusion Matrix for KNN:



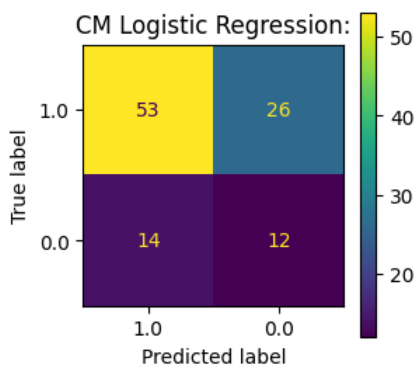
Out[10]:

	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.714286	0.825581	0.763441	0.898734	0.153846	0.898734	0.526290
1	Naive Bayes	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
2	Linear SVC	0.571429	0.697987	0.742857	0.658228	0.307692	0.658228	0.482960
3	Random Forest	0.733333	0.840909	0.762887	0.936709	0.115385	0.936709	0.526047
4	Perceptron	0.600000	0.700000	0.803279	0.620253	0.538462	0.620253	0.579357
5	KNN	0.600000	0.723684	0.753425	0.696203	0.307692	0.696203	0.501947

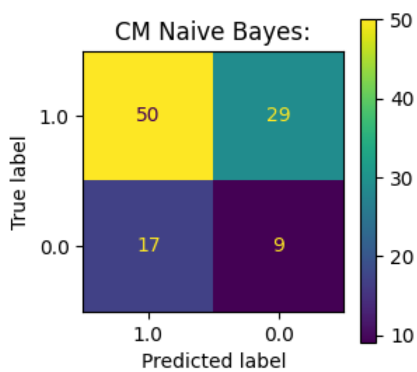
Text as Features and using Count Vectorizer

In [9]:
```
# Vectorize the text using CountVectorizer
vectorizer = CountVectorizer(min_df=5, max_df=0.8)
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

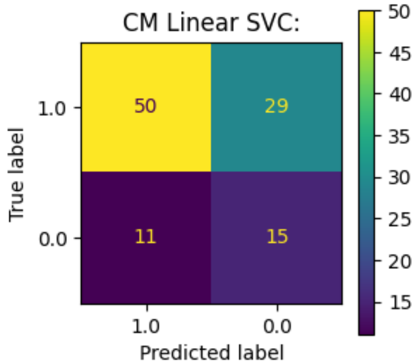
```
Confusion Matrix for Logistic Regression:
```



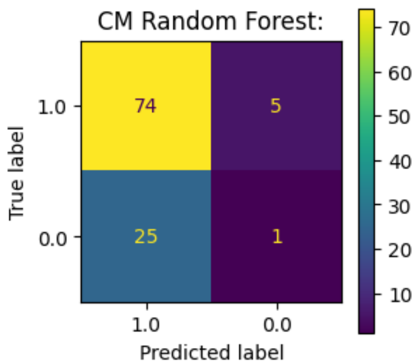

```
Confusion Matrix for Naive Bayes:
```



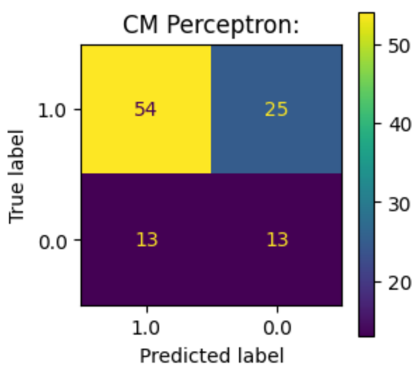

```
Confusion Matrix for Linear SVC:
```




```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
```



Out[9]:

	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.619048	0.726027	0.791045	0.670886	0.461538	0.670886	0.566212
1	Naive Bayes	0.561905	0.684932	0.746269	0.632911	0.346154	0.632911	0.489533
2	Linear SVC	0.619048	0.714286	0.819672	0.632911	0.576923	0.632911	0.604917
3	Random Forest	0.714286	0.831461	0.747475	0.936709	0.038462	0.936709	0.487585
4	Perceptron	0.638095	0.739726	0.805970	0.683544	0.500000	0.683544	0.591772

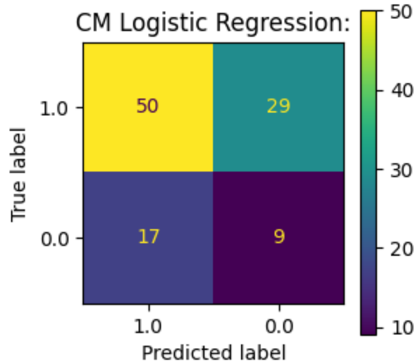
Text as Features and using TF-IDF Vectorizer and using Over and Under Sampling

In [11]:

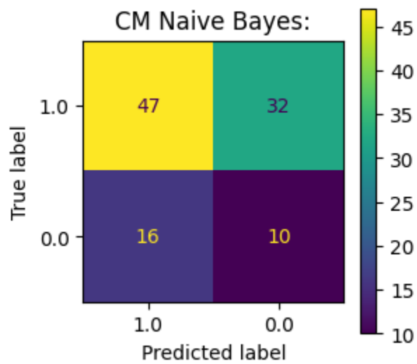
```
# USING IMBLEARN
from imblearn.over_sampling import SMOTE
from imblearn.under_sampling import RandomUnderSampler

vectorizer = TfidfVectorizer(min_df=5, max_df=0.8)
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)


# Resample the training data
print('--OVERSAMPLING--')
ros = SMOTE(random_state=0)
X_train_resampled, y_train_resampled = ros.fit_resample(X_train, y_train)
classifier = Classifier(X_train_resampled, X_test, y_train_resampled, y_test)
print(classifier)

print('--UNDERSAMPLING--')
```

```
ros = RandomUnderSampler(random_state=0)
X_train_resampled, y_train_resampled = ros.fit_resample(X_train, y_train)
classifier = Classifier(X_train_resampled, X_test, y_train_resampled, y_test)
print(classifier)
```

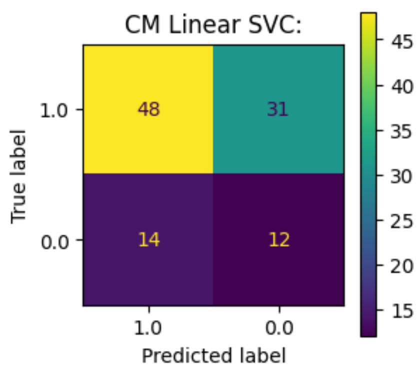
```
--OVERSAMPLING--
Confusion Matrix for Logistic Regression:
```



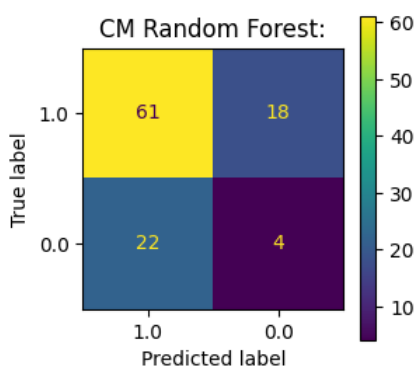

```
Confusion Matrix for Naive Bayes:
```



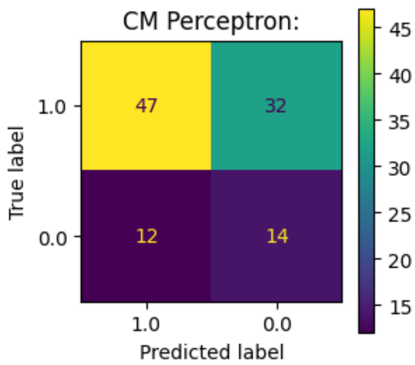

```
Confusion Matrix for Linear SVC:
```




```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
```



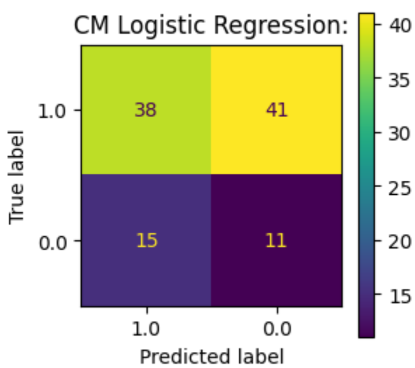
	classifier	accuracy	f1	precision	recall
0	Logistic Regression	0.561905	0.684932	0.746269	0.632911
1	Naive Bayes	0.542857	0.661972	0.746032	0.594937
2	Linear SVC	0.571429	0.680851	0.774194	0.607595
3	Random Forest	0.619048	0.753086	0.734940	0.772152
4	Perceptron	0.580952	0.681159	0.796610	0.594937

\

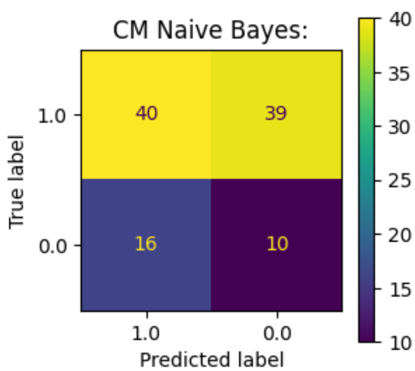
	True Negative Rate	True Positive Rate	auc
0	0.346154	0.632911	0.489533
1	0.384615	0.594937	0.489776
2	0.461538	0.607595	0.534567
3	0.153846	0.772152	0.462999
4	0.538462	0.594937	0.566699

--UNDERSAMPLING--

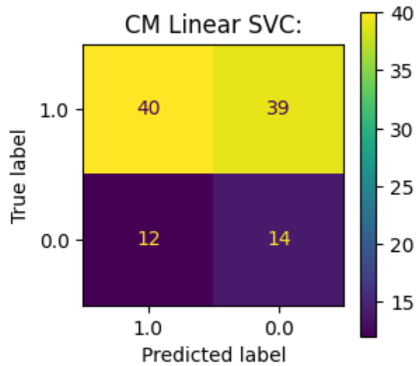
Confusion Matrix for Logistic Regression:



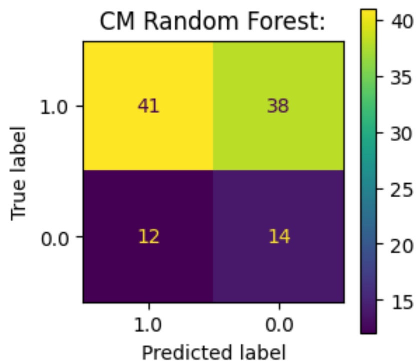
Confusion Matrix for Naive Bayes:



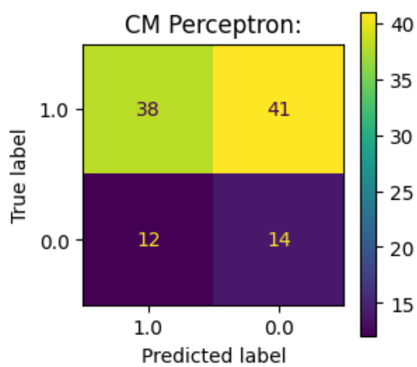
Confusion Matrix for Linear SVC:




```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
```




```
            classifier  accuracy        f1  precision    recall  \
0  Logistic Regression  0.466667  0.575758   0.716981  0.481013
1          Naive Bayes  0.476190  0.592593   0.714286  0.506329
2           Linear SVC  0.514286  0.610687   0.769231  0.506329
3        Random Forest  0.523810  0.621212   0.773585  0.518987
4           Perceptron  0.495238  0.589147   0.760000  0.481013

   True Negative Rate  True Positive Rate       auc
0            0.423077            0.481013  0.452045
1            0.384615            0.506329  0.445472
2            0.538462            0.506329  0.522395
3            0.538462            0.518987  0.528724
4            0.538462            0.481013  0.509737
```

Try using k-fold cross validation

In [33]:

```python
from sklearn.model_selection import cross_val_score

def Classifier_kfold(X, y):

    classifiers = {
        "Logistic Regression": LogisticRegression(max_iter=1000),
        "Naive Bayes": MultinomialNB(),
        "Linear SVC": LinearSVC(),
        "Random Forest": RandomForestClassifier(),
        "Perceptron": Perceptron(),
    }

    results = []
```

```python
    for classifier_name, classifier in classifiers.items():

        # Perform k-fold cross-validation
        scores = cross_val_score(classifier, X, y, cv=5, scoring='accuracy')  # 5-fold cross-validation
        # Add the scores to the results list
        results.append({
            'classifier': classifier_name,
            'mean_f1': scores.mean(),
            'std_f1': scores.std(),
        })

        print(f"f1 for {classifier_name}: {scores.mean()} (+/- {scores.std() * 2})")

    return pd.DataFrame(results)

# Vectorize the text using TF-IDF
vectorizer = TfidfVectorizer(min_df=5, max_df=0.7)
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
Classifier_kfold(X, y)
```

```
f1 for Logistic Regression: 0.6237912087912088 (+/- 0.008850077622725633)
f1 for Naive Bayes: 0.6353113553113553 (+/- 0.002783882783882774)
f1 for Linear SVC: 0.6083333333333334 (+/- 0.06005147912118134)
f1 for Random Forest: 0.6276373626373626 (+/- 0.03304313560378509)
f1 for Perceptron: 0.5853663003663004 (+/- 0.054826294118804415)
```

Out[33]:

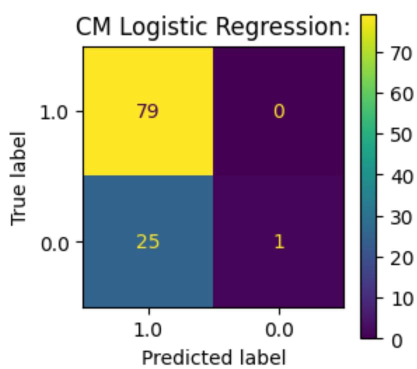
	classifier	mean_f1	std_f1
0	Logistic Regression	0.623791	0.004425
1	Naive Bayes	0.635311	0.001392
2	Linear SVC	0.608333	0.030026
3	Random Forest	0.627637	0.016522
4	Perceptron	0.585366	0.027413

Using ngrams

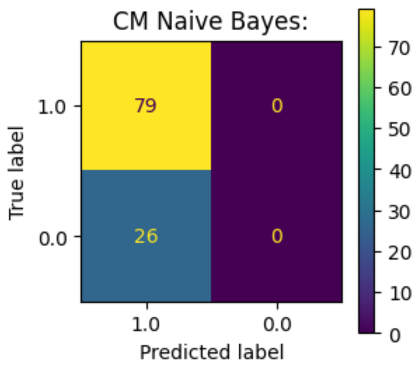
In [11]:

```python
# Vectorize the text using TF-IDF and bigrams
vectorizer = TfidfVectorizer(min_df=5, max_df=0.7, ngram_range =(2, 2))
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

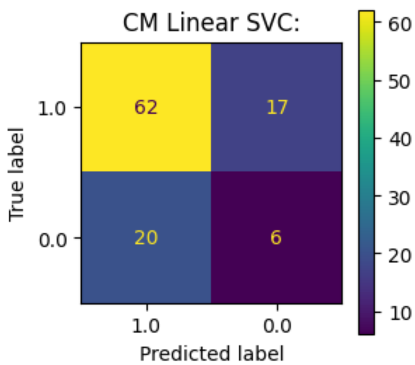
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01914151  0.05325384 -0.01408864 ... -0.01701203 -0.00579603
  -0.16882371]]
```



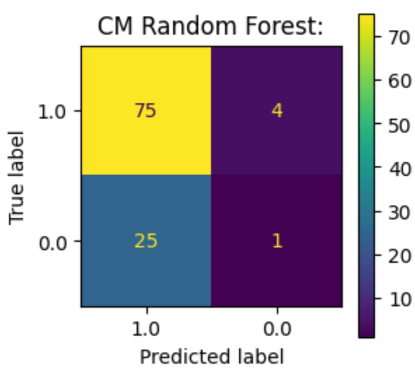

```
Confusion Matrix for Naive Bayes:
```



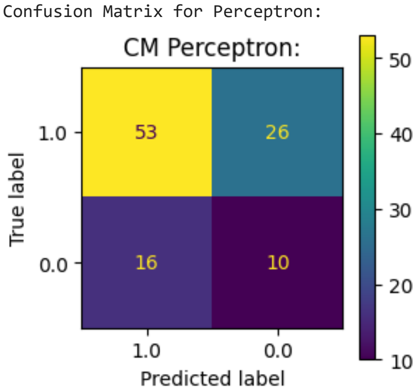
Confusion Matrix for Linear SVC:



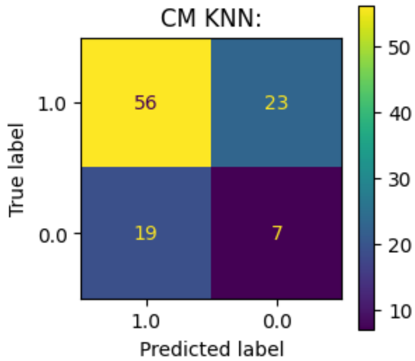
Confusion Matrix for Random Forest:



Confusion Matrix for Perceptron:



Confusion Matrix for KNN:



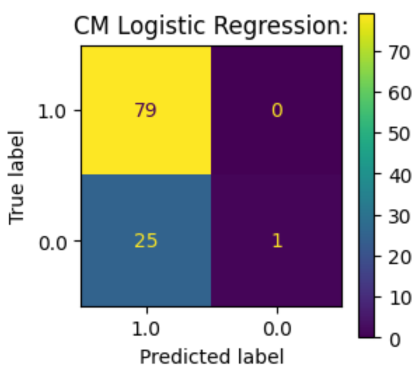
Out[11]:

	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.647619	0.770186	0.756098	0.784810	0.230769	0.784810	0.507790
3	Random Forest	0.723810	0.837989	0.750000	0.949367	0.038462	0.949367	0.493914
4	Perceptron	0.600000	0.716216	0.768116	0.670886	0.384615	0.670886	0.527751
5	KNN	0.600000	0.727273	0.746667	0.708861	0.269231	0.708861	0.489046

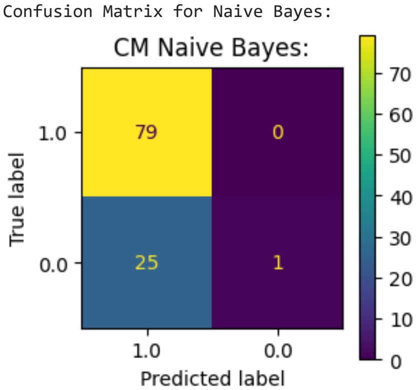
In [12]:

```
# Vectorize the text using TF-IDF: Trigrams
vectorizer = TfidfVectorizer(min_df=5, max_df=0.7, ngram_range =(3, 3))
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

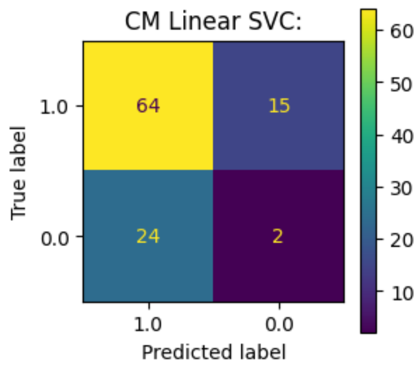
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[-0.09237814  0.07358038  0.09318226 ...  0.07050802  0.00746334
  -0.24805484]]
```



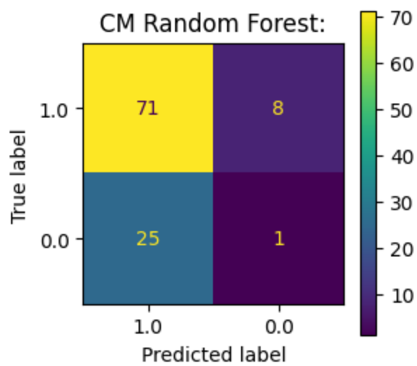

```
Confusion Matrix for Naive Bayes:
```



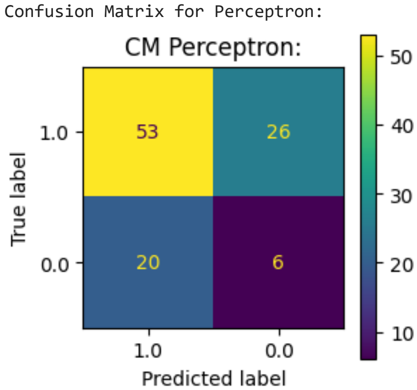

```
Confusion Matrix for Linear SVC:
```



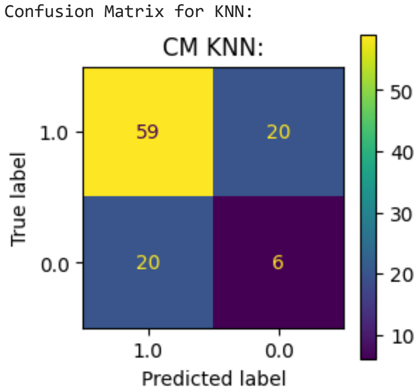

```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
```




```
Confusion Matrix for KNN:
```



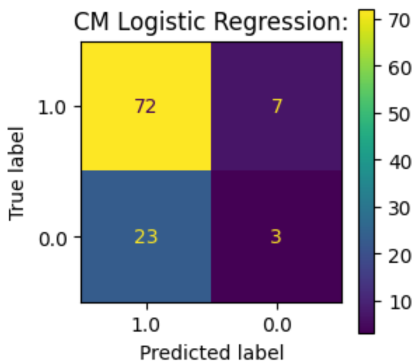
Out[12]:

	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
2	Linear SVC	0.628571	0.766467	0.727273	0.810127	0.076923	0.810127	0.443525
3	Random Forest	0.685714	0.811429	0.739583	0.898734	0.038462	0.898734	0.468598
4	Perceptron	0.561905	0.697368	0.726027	0.670886	0.230769	0.670886	0.450828
5	KNN	0.619048	0.746835	0.746835	0.746835	0.230769	0.746835	0.488802

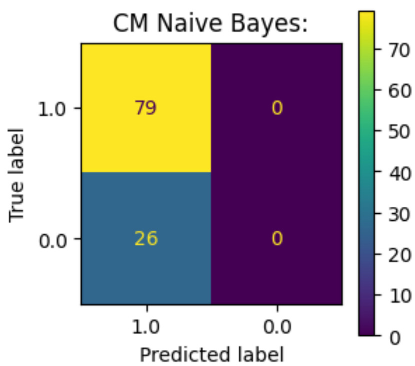
In [13]:

```python
# Vectorize the text using TF-IDF: range 1 to 3 grams
vectorizer = TfidfVectorizer(min_df=5, max_df=0.7, ngram_range =(1, 3))
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

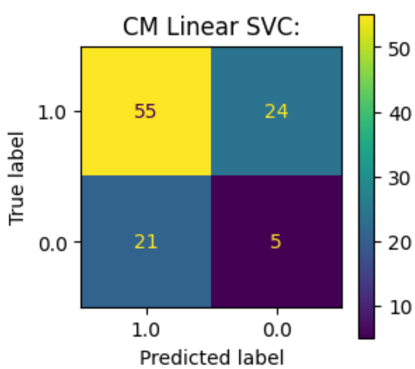
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.09887798  0.01125257  0.02364326 ...  0.02447635 -0.08093888
  -0.04026498]]
```



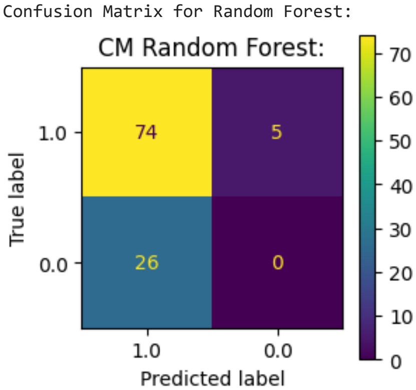

```
Confusion Matrix for Naive Bayes:
```



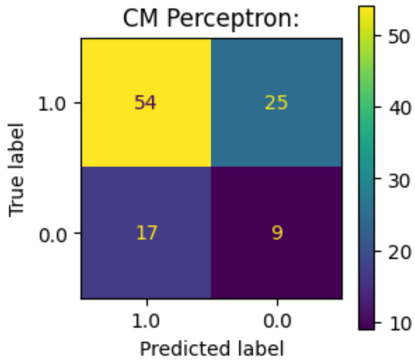

```
Confusion Matrix for Linear SVC:
```



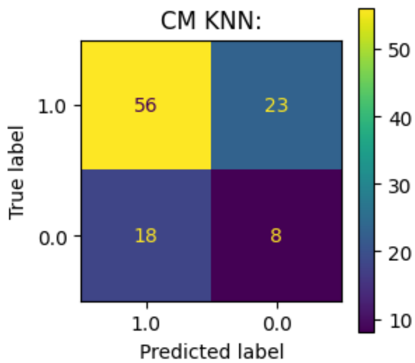

```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
```




```
Confusion Matrix for KNN:
```



Out[13]:

	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.714286	0.827586	0.757895	0.911392	0.115385	0.911392	0.513389
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.571429	0.709677	0.723684	0.696203	0.192308	0.696203	0.444255
3	Random Forest	0.704762	0.826816	0.740000	0.936709	0.000000	0.936709	0.468354
4	Perceptron	0.600000	0.720000	0.760563	0.683544	0.346154	0.683544	0.514849
5	KNN	0.609524	0.732026	0.756757	0.708861	0.307692	0.708861	0.508277

In [70]:

```
# Calculate The Baseline based on y_test
accuracy = y_test.value_counts()[1]/y_test.shape[0]
print('Accuracy: ', accuracy)
```

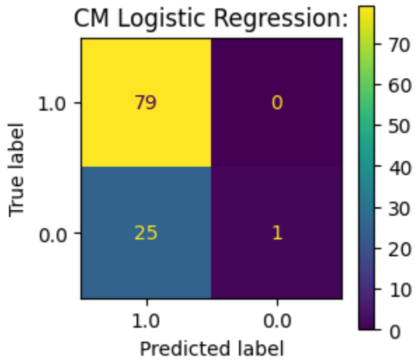
```
Accuracy:  0.7523809523809524
```

Using 'Text' + rep_pct + male_jpc + develop_time as the feature

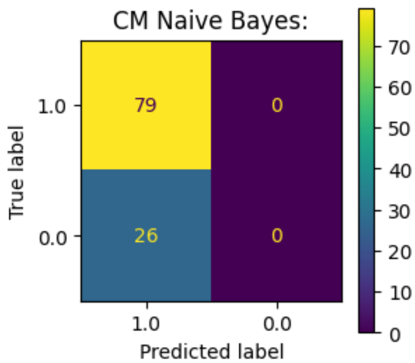
In [14]:

```
tfidf = TfidfVectorizer(min_df=5, max_df=0.8,ngram_range =(2, 2))
X_text = tfidf.fit_transform(df_rf['text'])
X_rep_pct = np.array(df_rf['rep_jpc']).reshape(-1, 1)
X_male_jpc = np.array(df_rf['male_jpc']).reshape(-1, 1)
X_dev_time = np.array(df_rf['develop_time']).reshape(-1, 1)
X_party = np.array(df_rf['party']).reshape(-1, 1)
y = df_rf['win_side']
# Horizontally stack the TF-IDF other features
X = np.hstack((X_text.toarray(), X_rep_pct, X_male_jpc, X_dev_time))

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

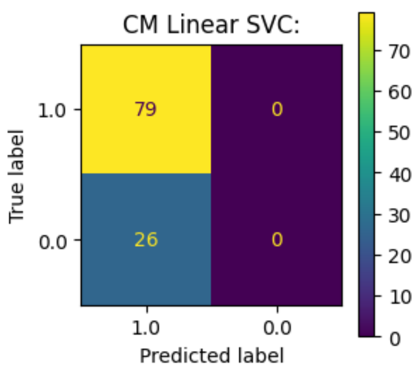
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01900358  0.05249416 -0.01398821 ...  0.01246409 -0.08228093
  -0.00045653]]
```



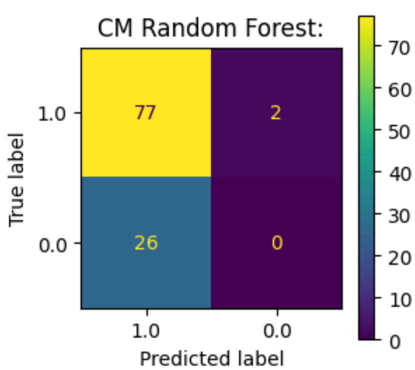

```
Confusion Matrix for Naive Bayes:
```



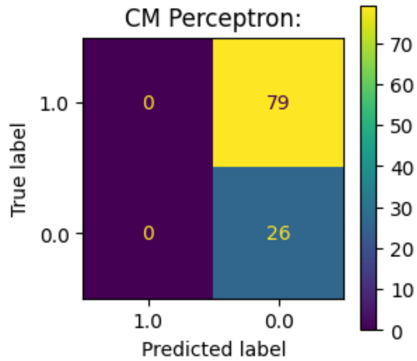

```
Confusion Matrix for Linear SVC:
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  warnings.warn(
```



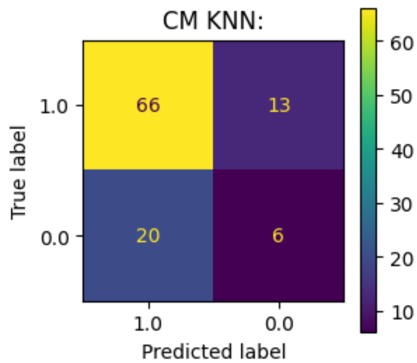

```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precis
ion is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```




```
Confusion Matrix for KNN:
```



Out[14]:

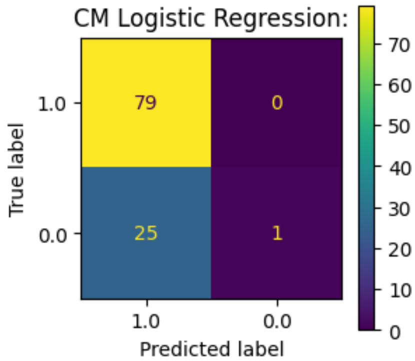
	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
3	Random Forest	0.733333	0.846154	0.747573	0.974684	0.000000	0.974684	0.487342
4	Perceptron	0.247619	0.000000	0.000000	0.000000	1.000000	0.000000	0.500000
5	KNN	0.685714	0.800000	0.767442	0.835443	0.230769	0.835443	0.533106

Using 'Text' + rep_pct + male_jpc as the feature

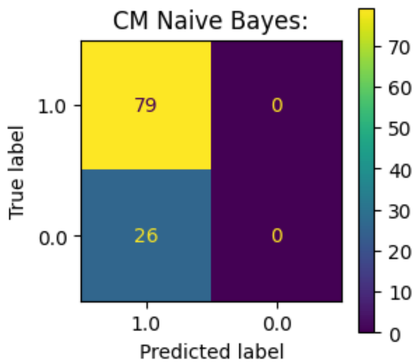
In [15]:

```
tfidf = TfidfVectorizer(min_df=5, max_df=0.8,ngram_range =(2, 2))
X_text = tfidf.fit_transform(df_rf['text'])
X_rep_pct = np.array(df_rf['rep_jpc']).reshape(-1, 1)
X_male_jpc = np.array(df_rf['male_jpc']).reshape(-1, 1)
X_dev_time = np.array(df_rf['develop_time']).reshape(-1, 1)
X_party = np.array(df_rf['party']).reshape(-1, 1)
y = df_rf['win_side']
# Horizontally stack the TF-IDF other features
X = np.hstack((X_text.toarray(), X_rep_pct, X_dev_time))

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01901738  0.05252966 -0.01400972 ... -0.16520139  0.01492379
  -0.00045276]]
```

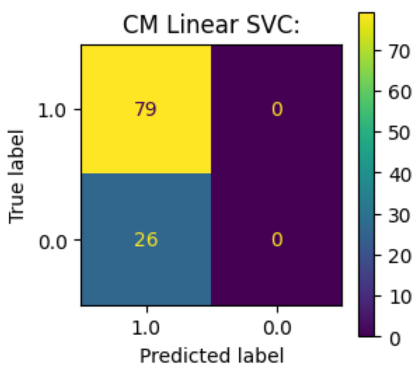


Confusion Matrix for Naive Bayes:

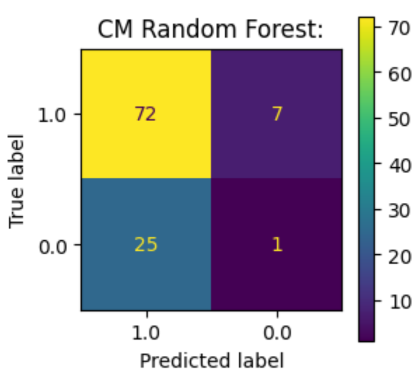


Confusion Matrix for Linear SVC:

```
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  warnings.warn(
```

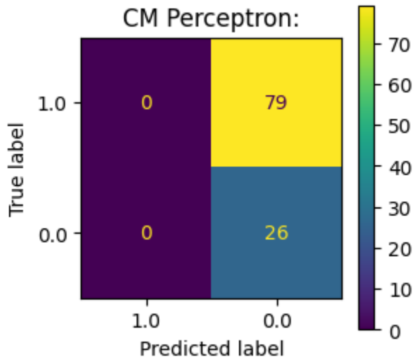


Confusion Matrix for Random Forest:

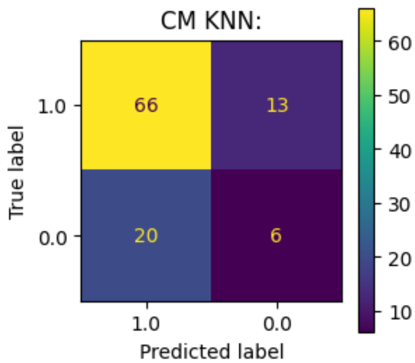


Confusion Matrix for Perceptron:

```
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precis
ion is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



Confusion Matrix for KNN:



Out[15]:

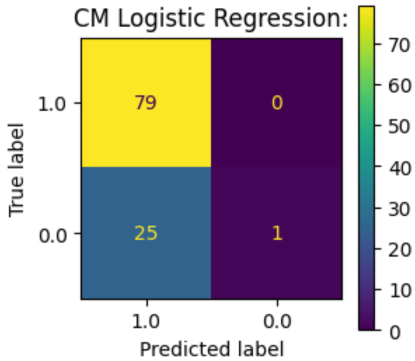
	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
3	Random Forest	0.695238	0.818182	0.742268	0.911392	0.038462	0.911392	0.474927
4	Perceptron	0.247619	0.000000	0.000000	0.000000	1.000000	0.000000	0.500000
5	KNN	0.685714	0.800000	0.767442	0.835443	0.230769	0.835443	0.533106

Using 'Text' + male_jpc + develop_time as the feature

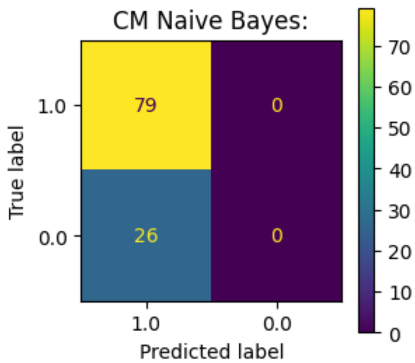
In [16]:

```
tfidf = TfidfVectorizer(min_df=5, max_df=0.8,ngram_range =(2, 2))
X_text = tfidf.fit_transform(df_rf['text'])
X_rep_pct = np.array(df_rf['rep_jpc']).reshape(-1, 1)
X_male_jpc = np.array(df_rf['male_jpc']).reshape(-1, 1)
X_dev_time = np.array(df_rf['develop_time']).reshape(-1, 1)
X_party = np.array(df_rf['party']).reshape(-1, 1)
y = df_rf['win_side']
# Horizontally stack the TF-IDF other features
X = np.hstack((X_text.toarray(), X_male_jpc, X_dev_time))

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01866398  0.05256018 -0.01407685 ... -0.16448145 -0.03192788
  -0.00044994]]
```

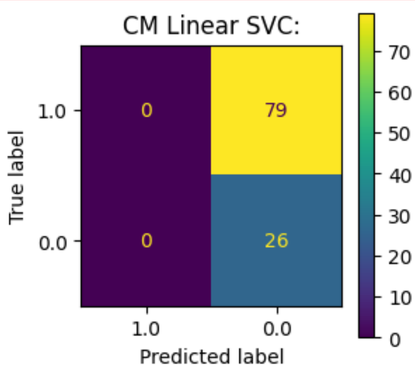



```
Confusion Matrix for Naive Bayes:
```

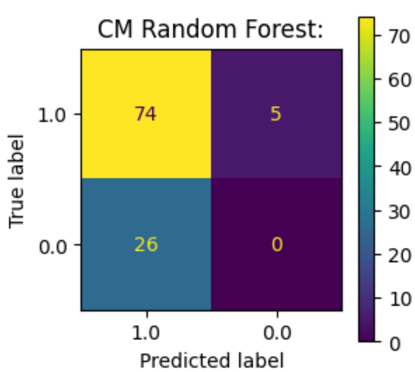



```
Confusion Matrix for Linear SVC:
```

```
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  warnings.warn(
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precis
ion is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```

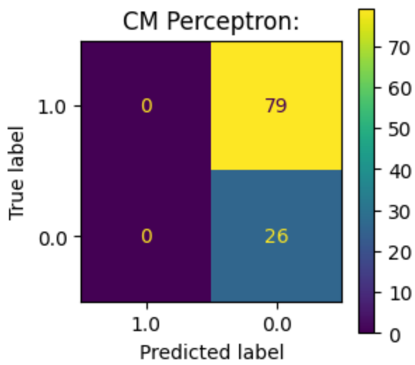



```
Confusion Matrix for Random Forest:
```

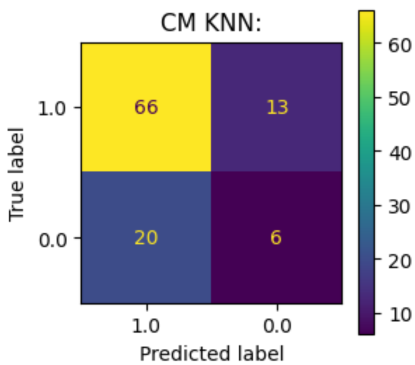



```
Confusion Matrix for Perceptron:
```

```
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precis
ion is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



Confusion Matrix for KNN:



Out[16]:

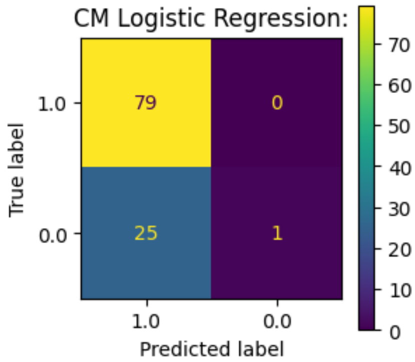
	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.247619	0.000000	0.000000	0.000000	1.000000	0.000000	0.500000
3	Random Forest	0.704762	0.826816	0.740000	0.936709	0.000000	0.936709	0.468354
4	Perceptron	0.247619	0.000000	0.000000	0.000000	1.000000	0.000000	0.500000
5	KNN	0.685714	0.800000	0.767442	0.835443	0.230769	0.835443	0.533106

Using 'Text' + rep_jpc as the feature

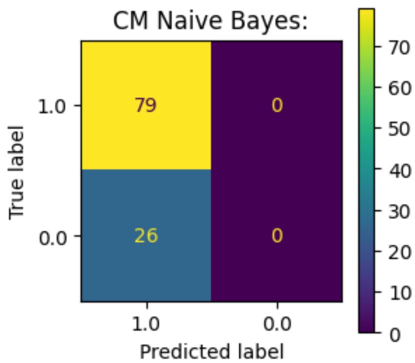
In [17]:

```
tfidf = TfidfVectorizer(min_df=5, max_df=0.8, ngram_range =(2, 2))
X_text = tfidf.fit_transform(df_rf['text'])
X_rep_pct = np.array(df_rf['rep_jpc']).reshape(-1, 1)
X_male_jpc = np.array(df_rf['male_jpc']).reshape(-1, 1)
X_dev_time = np.array(df_rf['develop_time']).reshape(-1, 1)
X_party = np.array(df_rf['party']).reshape(-1, 1)
y = df_rf['win_side']
# Horizontally stack the TF-IDF other features
X = np.hstack((X_text.toarray(), X_rep_pct))

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

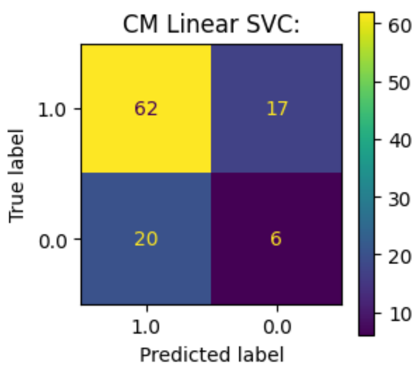
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 1.91723738e-02  5.28830096e-02 -1.40558302e-02 ... -5.77817776e-03
  -1.68158369e-01 -1.17107435e-04]]
```



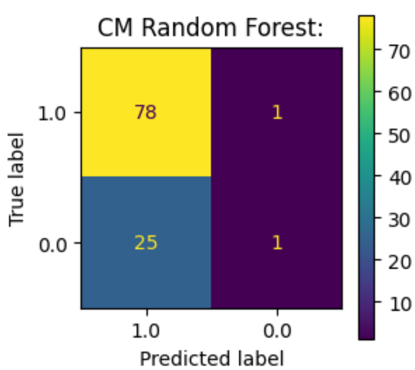

```
Confusion Matrix for Naive Bayes:
```



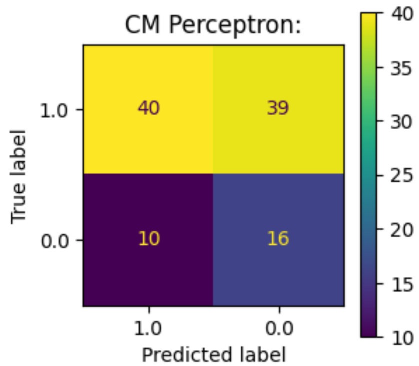

```
Confusion Matrix for Linear SVC:
```



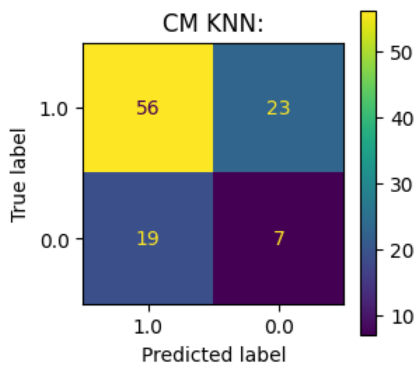

```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
```




```
Confusion Matrix for KNN:
```



Out[17]:

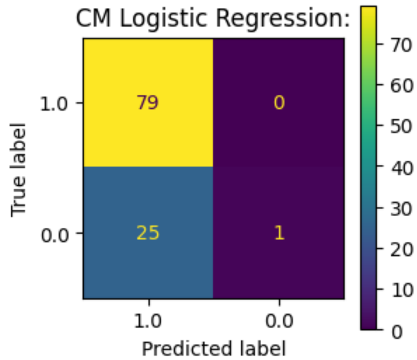
	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.647619	0.770186	0.756098	0.784810	0.230769	0.784810	0.507790
3	Random Forest	0.752381	0.857143	0.757282	0.987342	0.038462	0.987342	0.512902
4	Perceptron	0.533333	0.620155	0.800000	0.506329	0.615385	0.506329	0.560857
5	KNN	0.600000	0.727273	0.746667	0.708861	0.269231	0.708861	0.489046

Using 'Text' + male_jpc as the feature

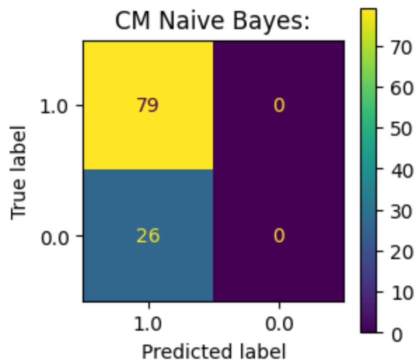
In [18]:

```
tfidf = TfidfVectorizer(min_df=5, max_df=0.8,ngram_range =(2, 2))
X_text = tfidf.fit_transform(df_rf['text'])
X_rep_pct = np.array(df_rf['rep_jpc']).reshape(-1, 1)
X_male_jpc = np.array(df_rf['male_jpc']).reshape(-1, 1)
X_dev_time = np.array(df_rf['develop_time']).reshape(-1, 1)
X_party = np.array(df_rf['party']).reshape(-1, 1)
y = df_rf['win_side']
# Horizontally stack the TF-IDF other features
X = np.hstack((X_text.toarray(), X_male_jpc))

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

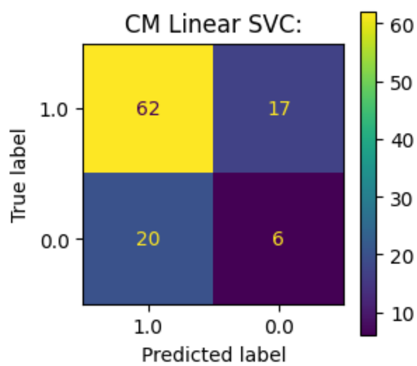
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01916319  0.05289112 -0.01406044 ... -0.00579865 -0.16836936
  -0.0928783 ]]
```



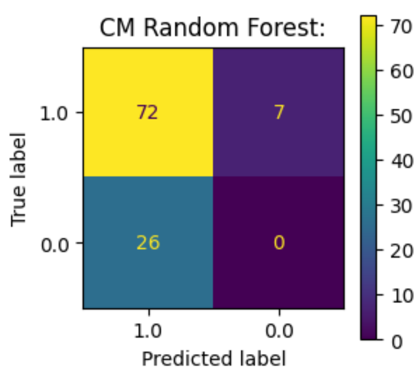
Confusion Matrix for Naive Bayes:



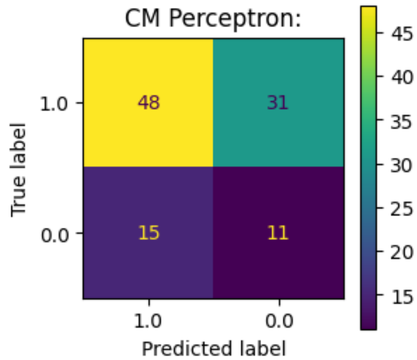
Confusion Matrix for Linear SVC:



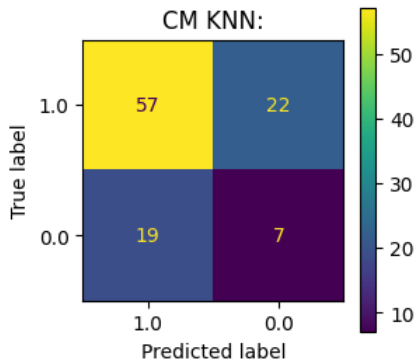
Confusion Matrix for Random Forest:



Confusion Matrix for Perceptron:




```
Confusion Matrix for KNN:
```



Out[18]:

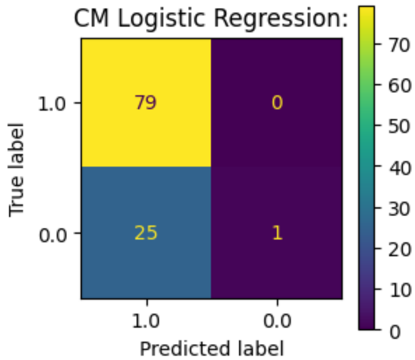
	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.647619	0.770186	0.756098	0.784810	0.230769	0.784810	0.507790
3	Random Forest	0.685714	0.813559	0.734694	0.911392	0.000000	0.911392	0.455696
4	Perceptron	0.561905	0.676056	0.761905	0.607595	0.423077	0.607595	0.515336
5	KNN	0.609524	0.735484	0.750000	0.721519	0.269231	0.721519	0.495375

Using 'Text' + dev_time as the feature

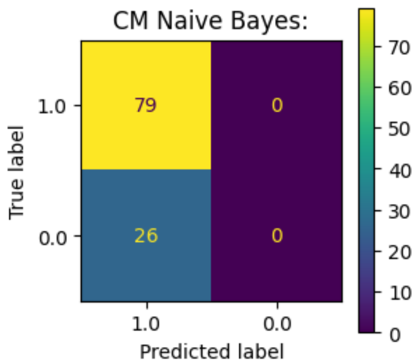
In [29]:

```
tfidf = TfidfVectorizer(min_df=5, max_df=0.8,ngram_range =(2, 2))
X_text = tfidf.fit_transform(df_rf['text'])
X_rep_pct = np.array(df_rf['rep_jpc']).reshape(-1, 1)
X_male_jpc = np.array(df_rf['male_jpc']).reshape(-1, 1)
X_dev_time = np.array(df_rf['develop_time']).reshape(-1, 1)
X_party = np.array(df_rf['party']).reshape(-1, 1)
y = df_rf['win_side']
# Horizontally stack the TF-IDF other features
X = np.hstack((X_text.toarray(), X_dev_time))

X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
```

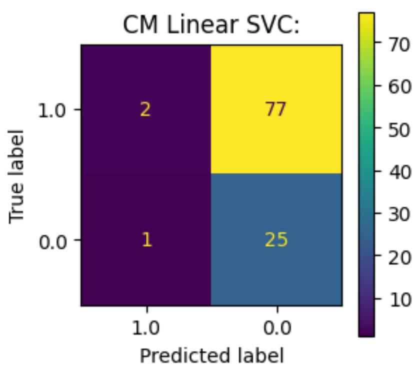
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01901232  0.05250654 -0.01401245 ... -0.00578631 -0.16533421
  -0.00045581]]
```



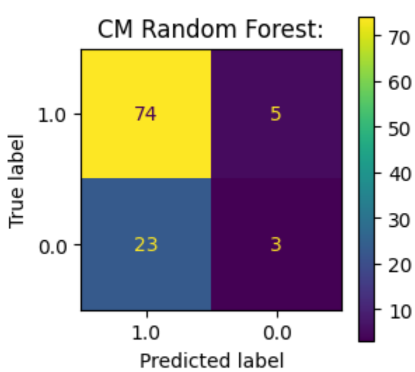

```
Confusion Matrix for Naive Bayes:
```



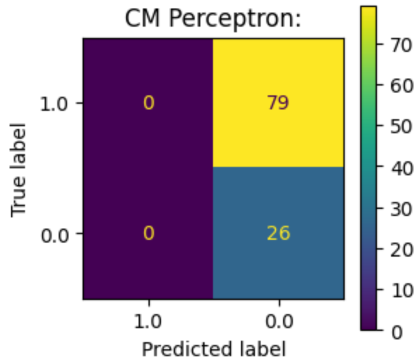

```
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  warnings.warn(
Confusion Matrix for Linear SVC:
```



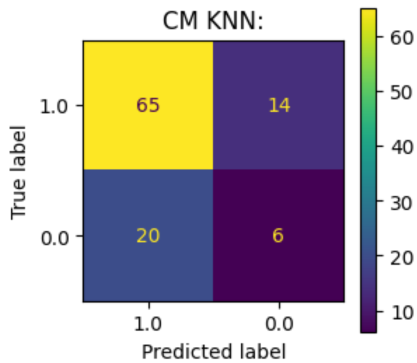

```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precis
ion is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```




```
Confusion Matrix for KNN:
```



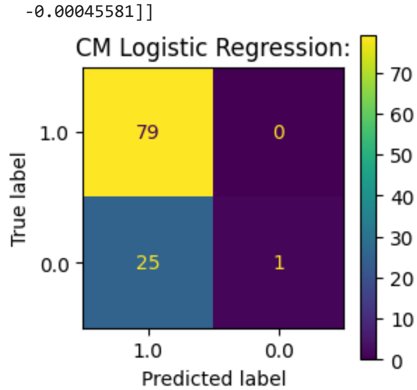
Out[29]:

	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.257143	0.048780	0.666667	0.025316	0.961538	0.025316	0.493427
3	Random Forest	0.733333	0.840909	0.762887	0.936709	0.115385	0.936709	0.526047
4	Perceptron	0.247619	0.000000	0.000000	0.000000	1.000000	0.000000	0.500000
5	KNN	0.676190	0.792683	0.764706	0.822785	0.230769	0.822785	0.526777

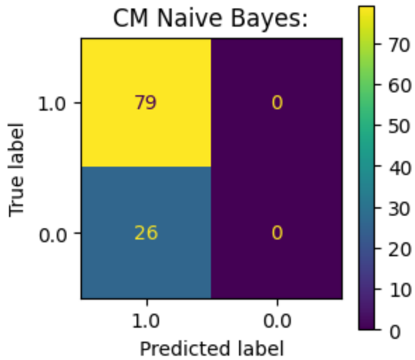
In [20]:

```python
# USING IMBLEARN
from imblearn.over_sampling import SMOTE
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier(X_train, X_test, y_train, y_test)
ros = SMOTE(random_state=0)
X_train_resampled, y_train_resampled = ros.fit_resample(X_train, y_train)
Classifier(X_train_resampled, X_test, y_train_resampled, y_test)
```

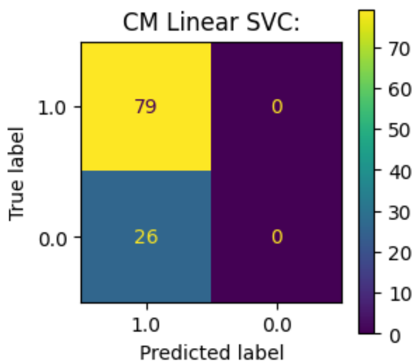
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01901232  0.05250654 -0.01401245 ... -0.00578631 -0.16533421
  -0.00045581]]
```



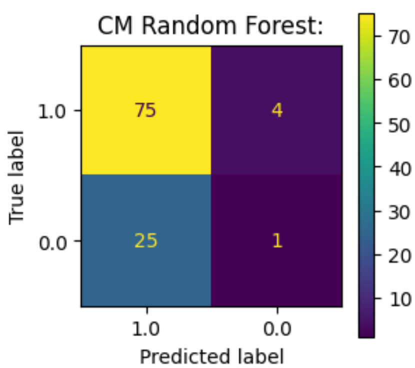

```
Confusion Matrix for Naive Bayes:
```



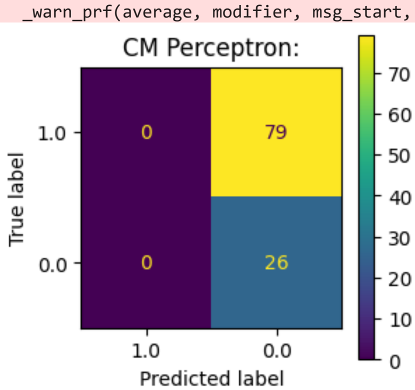

```
Confusion Matrix for Linear SVC:
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  warnings.warn(
```



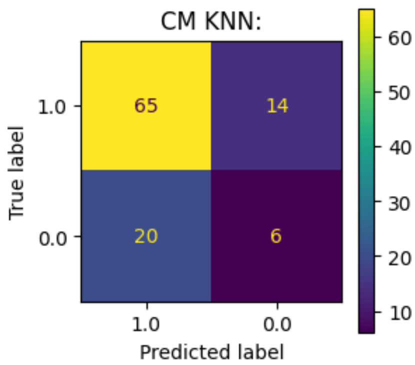

```
Confusion Matrix for Random Forest:
```



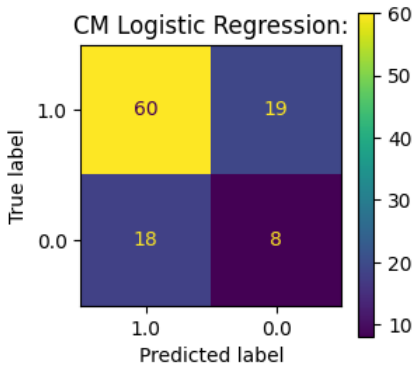

```
Confusion Matrix for Perceptron:
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\metrics\_classification.py:1344: UndefinedMetricWarning: Precis
ion is ill-defined and being set to 0.0 due to no predicted samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, msg_start, len(result))
```



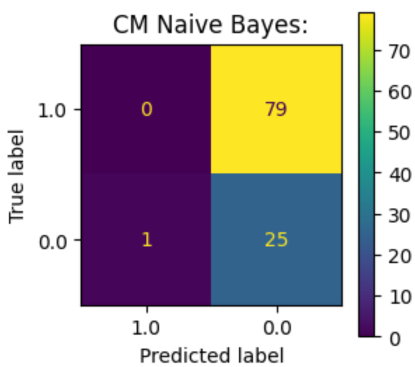

```
Confusion Matrix for KNN:
```



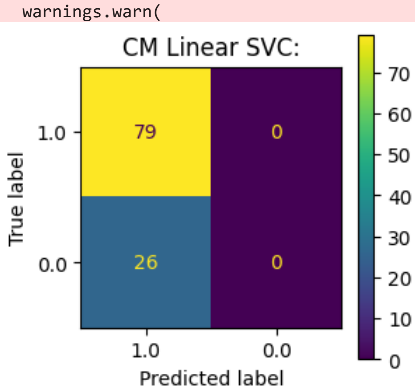

```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01863534  0.06180091 -0.01704493 ... -0.00818723 -0.12273915
  -0.00084728]]
```



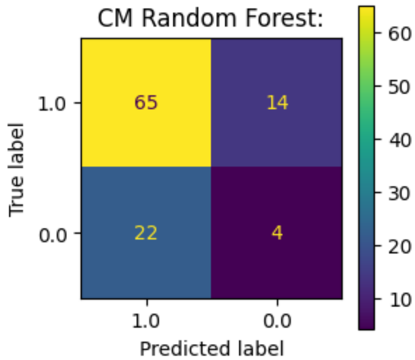

```
Confusion Matrix for Naive Bayes:
```



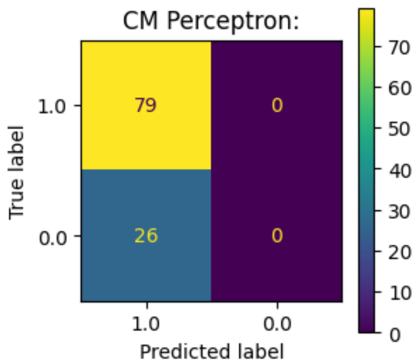

```
Confusion Matrix for Linear SVC:
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\sklearn\svm\_base.py:1244: ConvergenceWarning: Liblinear failed to conv
erge, increase the number of iterations.
  warnings.warn(
```



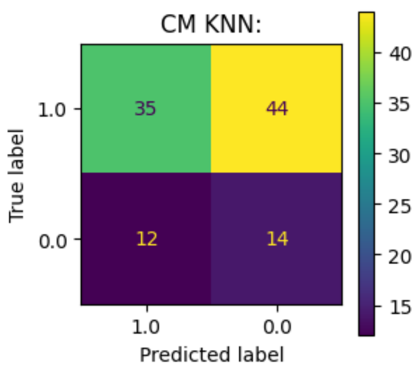

```
Confusion Matrix for Random Forest:
```



Confusion Matrix for Perceptron:



Confusion Matrix for KNN:



Out[20]:

	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.647619	0.764331	0.769231	0.759494	0.307692	0.759494	0.533593
1	Naive Bayes	0.238095	0.000000	0.000000	0.000000	0.961538	0.000000	0.480769
2	Linear SVC	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
3	Random Forest	0.657143	0.783133	0.747126	0.822785	0.153846	0.822785	0.488315
4	Perceptron	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
5	KNN	0.466667	0.555556	0.744681	0.443038	0.538462	0.443038	0.490750

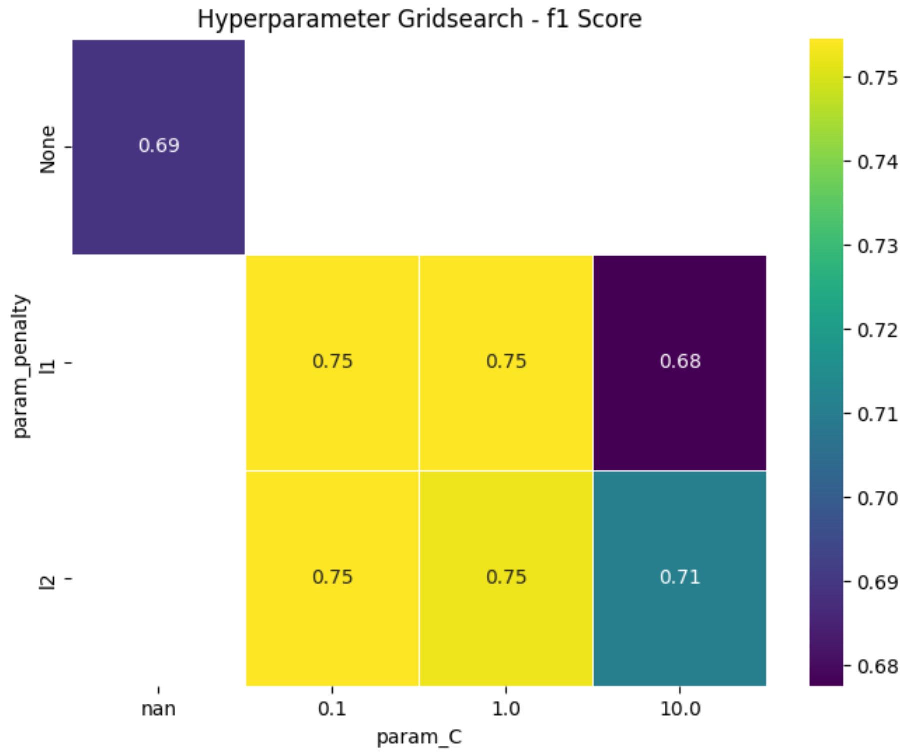
Check using different hyperparameter

In [57]:

```
from sklearn.model_selection import GridSearchCV
vectorizer = TfidfVectorizer(min_df=5, max_df=0.7, ngram_range =(2, 2))
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)

#load hyperparam
param_grid = [
    {'penalty': ['l1'], 'solver': ['liblinear'], 'C': [0.1, 1, 10]},
    {'penalty': ['l2'], 'solver': ['lbfgs'], 'C': [0.1, 1, 10]},
    {'penalty': [None], 'solver': ['lbfgs']},
]

grid = GridSearchCV(LogisticRegression(max_iter=1000), param_grid, cv=10, scoring='f1',
                    return_train_score=True, error_score=np.nan)
grid.fit(X_train, y_train)
```

```
results = pd.DataFrame(grid.cv_results_)
results['param_penalty'] = results['param_penalty'].astype('str')
scores_matrix = results.pivot(index='param_penalty', columns='param_C', values='mean_test_score')

plt.figure(figsize=(8, 6))
sns.heatmap(scores_matrix, annot=True, fmt=".2f", linewidths=.5, cmap='viridis')
plt.title('Hyperparameter Gridsearch - f1 Score')
plt.show()
```

```
C:\Users\rezar\AppData\Local\Temp\ipykernel_10152\1042704739.py:19: FutureWarning: In a future version, the Index constructor will
not infer numeric dtypes when passed object-dtype sequences (matching Series behavior)
  scores_matrix = results.pivot(index='param_penalty', columns='param_C', values='mean_test_score')
```



Trying using pretrained model

Try using pretrained model from transformers.

https://huggingface.co/models?pipeline_tag=text-classification&sort=downloads

In [38]:
```
import torch
import pandas as pd
from sklearn.model_selection import train_test_split
from sklearn.metrics import accuracy_score, precision_score, recall_score, f1_score
# from transformers import BertTokenizer, BertForSequenceClassification, Trainer, TrainingArguments
from transformers import DistilBertTokenizer, DistilBertForSequenceClassification, Trainer, TrainingArguments


# Load your data
data = pd.read_csv('text_clean.csv')

# Swapped 0 and 1 in win_side
# data['win_side'] = data['win_side'].apply(lambda x: 0 if x == 1 else 1)

# Split your data into training and testing sets
train_texts, test_texts, train_labels, test_labels = train_test_split(data['text'], data['win_side'], test_size=0.2, stratify=data

# Initialize the BERT tokenizer
# tokenizer = BertTokenizer.from_pretrained('bert-base-uncased')
tokenizer = DistilBertTokenizer.from_pretrained("distilbert-base-uncased")


# Tokenize the text data
train_encodings = tokenizer(train_texts.tolist(), truncation=True, padding=True)
test_encodings = tokenizer(test_texts.tolist(), truncation=True, padding=True)

# Create PyTorch Class from dataset
class SCOTUSDataset(torch.utils.data.Dataset):
    def __init__(self, encodings, labels):
```

```python
        self.encodings = encodings
        self.labels = labels

    def __getitem__(self, idx):
        item = {key: torch.tensor(val[idx]) for key, val in self.encodings.items()}
        item['labels'] = torch.tensor(self.labels[idx]).long()
        return item

    def __len__(self):
        return len(self.labels)

train_dataset = SCOTUSDataset(train_encodings, train_labels.tolist())
test_dataset = SCOTUSDataset(test_encodings, test_labels.tolist())

# Initialize the BERT model for sequence classification
# model = BertForSequenceClassification.from_pretrained('bert-base-uncased', num_labels=2)
# https://huggingface.co/distilbert-base-uncased-finetuned-sst-2-english
model = DistilBertForSequenceClassification.from_pretrained("distilbert-base-uncased")

# Set up training arguments
training_args = TrainingArguments(
    output_dir='./results',
    num_train_epochs=10,
    per_device_train_batch_size=2, #changed to 2 because the GPU
    per_device_eval_batch_size=4,
    warmup_steps=500,
    weight_decay=0.01,
    logging_dir='./logs',
    logging_steps=100,
    evaluation_strategy="steps",
    save_strategy="steps",
    save_steps=1000,
    load_best_model_at_end=True,
)

# Create the Trainer
trainer = Trainer(
    model=model,
    args=training_args,
    train_dataset=train_dataset,
    eval_dataset=test_dataset
)

# Train the model
trainer.train()

# Evaluate the model
predictions = trainer.predict(test_dataset)
predicted_labels = predictions.label_ids
y_pred = (predictions.predictions.argmax(-1)).tolist()

# Calculate performance metrics
accuracy = accuracy_score(test_labels, y_pred)
precision = precision_score(test_labels, y_pred)
recall = recall_score(test_labels, y_pred)
f1 = f1_score(test_labels, y_pred)

print(f"Accuracy: {accuracy:.4f}")
print(f"Precision: {precision:.4f}")
print(f"Recall: {recall:.4f}")
print(f"F1-Score: {f1:.4f}")
```

```
Some weights of the model checkpoint at distilbert-base-uncased were not used when initializing DistilBertForSequenceClassificatio
n: ['vocab_projector.weight', 'vocab_projector.bias', 'vocab_layer_norm.bias', 'vocab_transform.bias', 'vocab_transform.weight',
'vocab_layer_norm.weight']
- This IS expected if you are initializing DistilBertForSequenceClassification from the checkpoint of a model trained on another t
ask or with another architecture (e.g. initializing a BertForSequenceClassification model from a BertForPreTraining model).
- This IS NOT expected if you are initializing DistilBertForSequenceClassification from the checkpoint of a model that you expect
to be exactly identical (initializing a BertForSequenceClassification model from a BertForSequenceClassification model).
Some weights of DistilBertForSequenceClassification were not initialized from the model checkpoint at distilbert-base-uncased and
are newly initialized: ['pre_classifier.bias', 'classifier.weight', 'classifier.bias', 'pre_classifier.weight']
You should probably TRAIN this model on a down-stream task to be able to use it for predictions and inference.
C:\Users\rezar\anaconda3\envs\torch_cuda\lib\site-packages\transformers\optimization.py:391: FutureWarning: This implementation of
AdamW is deprecated and will be removed in a future version. Use the PyTorch implementation torch.optim.AdamW instead, or set `no_
deprecation_warning=True` to disable this warning
  warnings.warn(
```

[2080/2080 07:46, Epoch 10/10]

Step	Training Loss	Validation Loss
100	0.694300	0.668718
200	0.664300	0.656595
300	0.687600	0.654255
400	0.679200	0.660695
500	0.673700	0.654594
600	0.694700	0.651798
700	0.651100	0.674763
800	0.680400	0.689492
900	0.686100	0.665781
1000	0.670000	0.656918
1100	0.672700	0.657205
1200	0.656400	0.654485
1300	0.676800	0.665568
1400	0.671300	0.656507
1500	0.634500	0.665914
1600	0.684400	0.656613
1700	0.665900	0.655252
1800	0.660500	0.654917
1900	0.671700	0.654646
2000	0.632400	0.656990

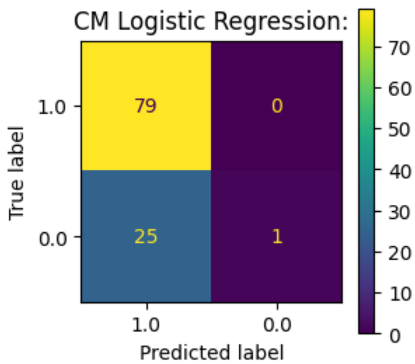
```
Accuracy: 0.6381
Precision: 0.6381
Recall: 1.0000
F1-Score: 0.7791
```

In [59]:
```python
def Classifier2(X_train, X_test, y_train, y_test):

    # Train and evaluate the classifiers
    classifiers = {
        "Logistic Regression": LogisticRegression(max_iter=1000, penalty='l2', C=1, solver='lbfgs'),
        "Naive Bayes": MultinomialNB(),
        "Linear SVC": LinearSVC(),
        "Random Forest": RandomForestClassifier(),
        "Perceptron": Perceptron(),
        "KNN": KNeighborsClassifier(n_neighbors=11)

    }
    results = []

    for classifier_name, classifier in classifiers.items():

        # Train the classifier
        classifier.fit(X_train, y_train)

        # Make predictions on the test set
        y_pred = classifier.predict(X_test)

        # Add the scores to the results dictionary
        results.append({
            'classifier': classifier_name,
            'accuracy': accuracy_score(y_test, y_pred),
            'f1': f1_score(y_test, y_pred),
            'precision': precision_score(y_test, y_pred),
            'recall': recall_score(y_test, y_pred),
            'True Negative Rate': confusion_matrix(y_test, y_pred)[0][0]/(confusion_matrix(y_test, y_pred)[0][0]+confusion_matrix(
            'True Positive Rate': confusion_matrix(y_test, y_pred)[1][1]/(confusion_matrix(y_test, y_pred)[1][1]+confusion_matrix(
            'auc': roc_auc_score(y_test, y_pred)
        })

        # Make a confusion matrix
        print(f"Confusion Matrix for {classifier_name}:")

        if classifier_name == "Logistic Regression":
```

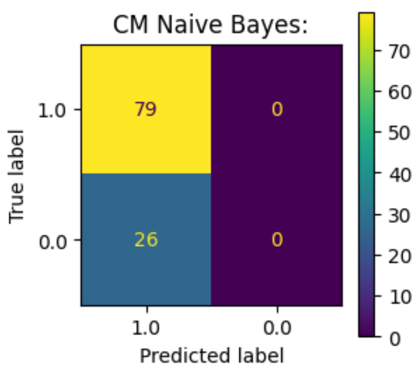
```
            print("Coefficients: \n", classifier.coef_)

        cm = confusion_matrix(y_test, y_pred, labels=y_test.unique())
        disp = ConfusionMatrixDisplay(confusion_matrix=cm, display_labels=y_test.unique())
        fig, ax = plt.subplots(figsize=(3, 3))
        ax.set_title(f"CM {classifier_name}:")
        disp.plot(ax=ax)
        plt.show()
    return pd.DataFrame(results)
```

In [60]:
```
X, y = Vectorize(vectorizer, df_rf['text'], df_rf['win_side'])
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=55)
Classifier2(X_train, X_test, y_train, y_test)
```

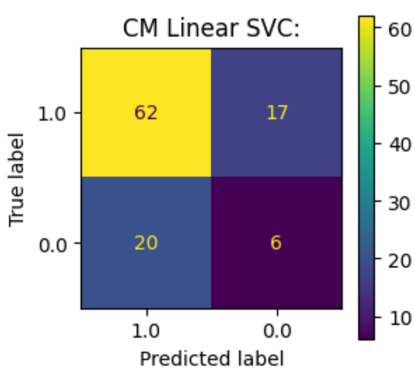
```
Confusion Matrix for Logistic Regression:
Coefficients:
 [[ 0.01914151  0.05325384 -0.01408864 ... -0.01701203 -0.00579603
  -0.16882371]]
```



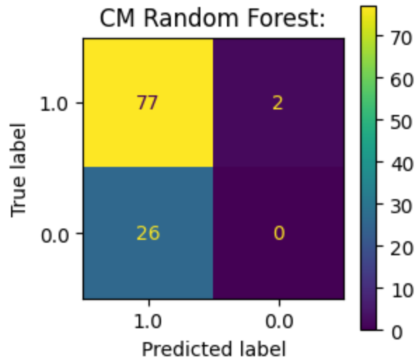

```
Confusion Matrix for Naive Bayes:
```



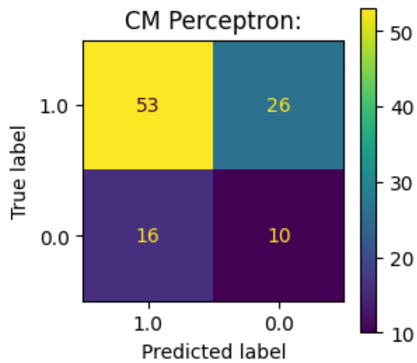

```
Confusion Matrix for Linear SVC:
```



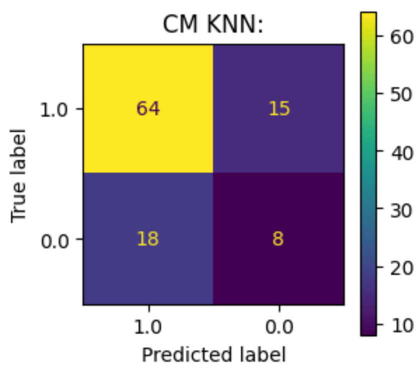

```
Confusion Matrix for Random Forest:
```




```
Confusion Matrix for Perceptron:
```




```
Confusion Matrix for KNN:
```



Out[60]:

	classifier	accuracy	f1	precision	recall	True Negative Rate	True Positive Rate	auc
0	Logistic Regression	0.761905	0.863388	0.759615	1.000000	0.038462	1.000000	0.519231
1	Naive Bayes	0.752381	0.858696	0.752381	1.000000	0.000000	1.000000	0.500000
2	Linear SVC	0.647619	0.770186	0.756098	0.784810	0.230769	0.784810	0.507790
3	Random Forest	0.733333	0.846154	0.747573	0.974684	0.000000	0.974684	0.487342
4	Perceptron	0.600000	0.716216	0.768116	0.670886	0.384615	0.670886	0.527751
5	KNN	0.685714	0.795031	0.780488	0.810127	0.307692	0.810127	0.558909

In [ ]: