Assignment1

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1 Assignment 1: Advanced NLP

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1.1 Environment setup

Install required packages `!pip install -r requirements.txt`

Download spaCy model (required for dependency parsing) `!python -m spacy download en_core_web_md`

If you don't use the requirements.txt file, here are the main dependencies: `!pip install pandas spacy scikit-learn matplotlib seaborn tqdm nltk benepar`

1.2 Import packages

[39]:
```
import pandas as pd
import spacy
from spacy.tokens import Doc
import benepar
from nltk.tree import Tree
from spacy import displacy
import os, logging
from sklearn.preprocessing import OneHotEncoder
from tqdm import tqdm
import numpy as np
from sklearn.linear_model import LogisticRegression
from sklearn.metrics import accuracy_score, classification_report,␣
↪precision_score, recall_score, f1_score
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.metrics import confusion_matrix
import numpy as np
from matplotlib.colors import LinearSegmentedColormap, LogNorm
from sklearn.model_selection import GridSearchCV
from sklearn.preprocessing import LabelEncoder
from scipy.sparse import hstack
import joblib
```

1.3 Data preprocessing

1.3.1 Process the conllu data

Make class that takes in a .conllu file and returns a dictionary of dataframes, where each dataframe contains the universal probbank data for a sentence.

[2]:
```
class ConlluProcessor:

    def __init__(self, file_path): # initialize the class with the file path
        self.file_path = file_path # store the file path
        self.conllu_data = self.read_conllu_file() # read the conllu file and␣
↪store the data

    def read_conllu_file(self): # define a method to read the conllu file
        """
        reads the conllu file and returns a list of sentences.
        """
        with open(self.file_path, 'r', encoding='utf-8') as file: # open the␣
↪file with utf-8 encoding
            data = file.read() # read the file content
        return data.split('\n\n') # split the content into sentences

    def sentence_to_dataframe(self, sentence_conllu): # define a method to␣
↪convert a sentence to a dataframe
        """
        converts a sentence in conllu format to a dataframe.
        """
        columns = ["ID", "WORD", "LEMMA", "POS-UNIV", "POS", "MORPH", "HEAD", ␣
↪# define the column names
                   "BASIC-DEP", "ENHANCED-DEP", "MISC", "PREDICATE"] # continue␣
↪defining column names
        rows = [] # initialize an empty list for rows
        sentence_text = '' # initialize an empty string for sentence text
        for row in sentence_conllu.split('\n'): # iterate over each row in the␣
↪sentence
            if row and row[0].isdigit(): # check if the row is not empty and␣
↪starts with a digit
                rows.append(row.split('\t')) # split the line by tab and add to␣
↪rows
            elif row and row[2] == 't': # check if the row is not empty and the␣
↪third character is 't'
                sentence_text = (row.split('= ')[1]) # extract the sentence text

        extra_columns = ["LABELS-P" + str(i+1) for i in range(len(rows[0]) -␣
↪len(columns))] if rows else [] # create extra columns if needed
```

```
        df = pd.DataFrame(rows, columns=columns + extra_columns) # create a␣
↪dataframe with the rows and columns

        if sentence_text != '': # check if sentence text is not empty
            return df, sentence_text # return the dataframe and sentence text
        else: # if sentence text is empty
            return None # return None

    def conllu_to_dataframes(self): # define a method to convert conllu data to␣
↪dataframes
        """
        converts a list of sentences in conllu format to a dictionary of␣
↪dataframes, where each dataframe contains the universal probbank data for a␣
↪sentence.
        """
        dictionary = {} # initialize an empty dictionary
        for item in self.conllu_data: # iterate over each item in conllu data
            output = self.sentence_to_dataframe(item) # convert the item to a␣
↪dataframe
            if output == None: # check if the output is None
                continue # skip to the next item
            else: # if output is not None
                dataframe, sentence_text = output # unpack the output
                dictionary[sentence_text] = dataframe # add the dataframe to␣
↪the dictionary with sentence_text as the key
        return dictionary # return the dictionary
```

Process test, dev and train data

[3]:
```
train_path = './en_ewt-up-train.conllu'
test_path = './en_ewt-up-test.conllu'
dev_path = './en_ewt-up-dev.conllu'

train_processor = ConlluProcessor(train_path)
test_processor = ConlluProcessor(test_path)
dev_processor = ConlluProcessor(dev_path)

train_dataframes = train_processor.conllu_to_dataframes()
test_dataframes = test_processor.conllu_to_dataframes()
dev_dataframes = dev_processor.conllu_to_dataframes()
```

1.3.2 Inspect the data

Get the number of sentences in the training and test data, and the average number of words per sentence, average number of predicates per sentence.

[4]:
```
print(f"Number of sentences in training data: {len(train_dataframes)}")

print(f"Number of sentences in test data: {len(test_dataframes)}")

print(f"Number of sentences in dev data: {len(dev_dataframes)}")
train_total_tokens = sum(len(df) for df in train_dataframes.values())
print(f"Total number of tokens in training data: {train_total_tokens}")

test_total_tokens = sum(len(df) for df in test_dataframes.values())
print(f"Total number of tokens in test data: {test_total_tokens}")

dev_total_tokens = sum(len(df) for df in dev_dataframes.values())
print(f"Total number of tokens in dev data: {dev_total_tokens}")

train_total_predicates = sum((df['PREDICATE'] != '_').sum() for df in␣
↪train_dataframes.values())
train_avg_predicates = train_total_predicates / len(train_dataframes)
print(f"Average number of predicates per sentence in training data:␣
↪{train_avg_predicates:.2f}")

test_total_predicates = sum((df['PREDICATE'] != '_').sum() for df in␣
↪test_dataframes.values())
test_avg_predicates = test_total_predicates / len(test_dataframes)
print(f"Average number of predicates per sentence in test data:␣
↪{test_avg_predicates:.2f}")

dev_total_predicates = sum((df['PREDICATE'] != '_').sum() for df in␣
↪dev_dataframes.values())
dev_avg_predicates = dev_total_predicates / len(dev_dataframes)
print(f"Average number of predicates per sentence in dev data:␣
↪{dev_avg_predicates:.2f}")
```

```
Number of sentences in training data: 11734
Number of sentences in test data: 1971
Number of sentences in dev data: 1914
Total number of tokens in training data: 199246
Total number of tokens in test data: 24728
Total number of tokens in dev data: 24906
Average number of predicates per sentence in training data: 3.36
Average number of predicates per sentence in test data: 2.45
Average number of predicates per sentence in dev data: 2.67
```

View last item of train data

[5]:
```
last_key = list(train_dataframes.keys())[-1] #sentence text
print(last_key)
train_dataframes[last_key] #dataframe
```

I will never return there again (and now have some serious doubts about the quality of work they actually performed on my car).

[5]:

	ID	WORD	LEMMA	POS-UNIV	POS	\
0	1	I	I	PRON	PRP	
1	2	will	will	AUX	MD	
2	3	never	never	ADV	RB	
3	4	return	return	VERB	VB	
4	5	there	there	ADV	RB	
5	6	again	again	ADV	RB	
6	7	(	(	PUNCT	-LRB-	
7	8	and	and	CCONJ	CC	
8	9	now	now	ADV	RB	
9	10	have	have	VERB	VBP	
10	11	some	some	DET	DT	
11	12	serious	serious	ADJ	JJ	
12	13	doubts	doubt	NOUN	NNS	
13	14	about	about	ADP	IN	
14	15	the	the	DET	DT	
15	16	quality	quality	NOUN	NN	
16	17	of	of	ADP	IN	
17	18	work	work	NOUN	NN	
18	19	they	they	PRON	PRP	
19	20	actually	actually	ADV	RB	
20	21	performed	perform	VERB	VBD	
21	22	on	on	ADP	IN	
22	23	my	my	PRON	PRP$	
23	24	car	car	NOUN	NN	
24	25	)	)	PUNCT	-RRB-	
25	26	.	.	PUNCT	.	

	MORPH	HEAD	BASIC-DEP	\
0	Case=Nom|Number=Sing|Person=1|PronType=Prs	4	nsubj	
1	VerbForm=Fin	4	aux	
2	_	4	advmod	
3	VerbForm=Inf	0	root	
4	PronType=Dem	4	advmod	
5	_	4	advmod	
6	_	4	punct	
7	_	10	cc	
8	_	10	advmod	
9	Mood=Ind|Tense=Pres|VerbForm=Fin	4	conj	
10	_	13	det	
11	Degree=Pos	13	amod	
12	Number=Plur	10	obj	
13	_	16	case	
14	Definite=Def|PronType=Art	16	det	

15	Number=Sing	13	nmod
16	_	18	case
17	Number=Sing	16	nmod
18	Case=Nom|Number=Plur|Person=3|PronType=Prs	21	nsubj
19	_	21	advmod
20	Mood=Ind|Tense=Past|VerbForm=Fin	18	acl:relcl
21	_	24	case
22	Number=Sing|Person=1|Poss=Yes|PronType=Prs	24	nmod:poss
23	Number=Sing	21	obl
24	_	4	punct
25	_	4	punct

	ENHANCED-DEP	MISC	PREDICATE	LABELS-P1	LABELS-P2	LABELS-P3	\
0	4:nsubj|10:nsubj	_	_	ARG1	_	ARG0	
1	4:aux	_	_	ARGM-MOD	_	_	
2	4:advmod	_	_	ARGM-NEG	_	_	
3	0:root	_	return.01	V	_	_	
4	4:advmod	_	_	ARG4	_	_	
5	4:advmod	_	_	ARGM-TMP	_	_	
6	4:punct	SpaceAfter=No	_	_	_	_	
7	10:cc	_	_	_	_	_	
8	10:advmod	_	_	_	_	ARGM-TMP	
9	4:conj:and	_	have.LV	_	V	ARGM-LVB	
10	13:det	_	_	_	_	_	
11	13:amod	_	_	_	_	ARGM-ADJ	
12	10:obj	_	doubt.01	_	ARGM-PRR	V	
13	16:case	_	_	_	_	_	
14	16:det	_	_	_	_	_	
15	13:nmod:about	_	_	_	_	ARG1	
16	18:case	_	_	_	_	_	
17	16:nmod:of	_	work.01	_	_	_	
18	21:nsubj	_	_	_	_	_	
19	21:advmod	_	_	_	_	_	
20	18:acl:relcl	_	perform.LV	_	_	_	
21	24:case	_	_	_	_	_	
22	24:nmod:poss	_	_	_	_	_	
23	21:obl:on	SpaceAfter=No	_	_	_	_	
24	4:punct	SpaceAfter=No	_	_	_	_	
25	4:punct	_	_	_	_	_	

	LABELS-P4	LABELS-P5
0	_	_
1	_	_
2	_	_
3	_	_
4	_	_
5	_	_

```
6          _         _
7          _         _
8          _         _
9          _         _
10         _         _
11         _         _
12         _         _
13         _         _
14         _         _
15         _         _
16         _         _
17         V  ARGM-PRR
18      ARG0         _
19  ARGM-ADV         _
20  ARGM-LVB         V
21         _         _
22         _         _
23      ARG1         _
24         _         _
25         _         _
```

1.3.3 Separating tables with multiple predicates

Ensuring each table only contains one predicate. Also adding a label: format is {predicate}_{sentence} for dictionary keys and removing sentences with no predicates.

[6]:
```
def extract_predicates(df):
    """
    Extracts predicates from a dataframe and returns a list of tuples, where␣
↪each tuple contains the predicate string and dataframe (duplicate predicate␣
↪labels).
    """

    output_dfs = []  # list to store output dataframes
    base_cols = list(df.loc[:, "ID":"MISC"].columns)  # columns to keep in the␣
↪output
    for col in df.columns:
        if col in base_cols or col == "PREDICATE":  # skip base columns and␣
↪PREDICATE column
            continue

        v_indices = df.index[df[col] == "V"].tolist()  # find indices where the␣
↪column has 'V'
        for idx in v_indices:
            temp_df = df[base_cols + ["PREDICATE", col]].copy()  # create a␣
↪temporary dataframe
```

```
            temp_df.rename(columns={col: "LABELS-P0"}, inplace=True)  # rename␣
↪the column to LABELS-P0
            predicate_string = temp_df.loc[idx, "PREDICATE"]  # get the␣
↪predicate string
            temp_df.loc[temp_df.index != idx, "PREDICATE"] = "_"  # set␣
↪PREDICATE to '_' for non-matching indices
            temp_df = temp_df[base_cols + ["PREDICATE", "LABELS-P0"]]  #␣
↪reorder columns
            output_dfs.append((predicate_string, temp_df))  # append the tuple␣
↪to the output list

    return output_dfs  # return the list of tuples

def separate_label_predicates(dataframes):
    """
    Separates predicates from a dataframe and returns a dictionary of␣
↪dataframes, where each key (sentence) starts with the predicate label.
    Completes the separation of predicates for all dataframes in the dictionary.
    """

    separated_dataframes = {}  # dictionary to store separated dataframes
    for sentence, df in dataframes.items():
        n_predicates = (df == 'V').sum().sum()  # count the number of predicates

        if n_predicates > 1:  # if more than one predicate
            output_dfs = extract_predicates(df)  # extract predicates
            for predicate_string, separated_df in output_dfs:
                separated_dataframes[predicate_string+"_"+sentence] =␣
↪separated_df  # add to dictionary
        elif n_predicates == 0:  # no predicate we do not include it
            continue
            #separated_dataframes["0_"+sentence] = df  # add to dictionary with␣
↪label 0
        else:  # exactly one predicate
            predicate_string = df.loc[df['PREDICATE'] != '_', 'PREDICATE'].
↪values[0]  # get the predicate string
            separated_dataframes[predicate_string+"_"+sentence] = df  # add to␣
↪dictionary
            df.rename(columns={"LABELS-P1": "LABELS-P0"}, inplace=True)  #␣
↪rename column for consistency

    return separated_dataframes  # return the dictionary of separated dataframes
```

Apply separating predicates to all dataframes.

[7]:
```
processed_test_dataframes=separate_label_predicates(test_dataframes)

processed_train_dataframes=separate_label_predicates(train_dataframes)

processed_dev_dataframes=separate_label_predicates(dev_dataframes)
```

Inspect the data after separating predicates (each sentence has only one predicate as sentences with multiple predicates have been separated and sentences with no predicates have been removed)

[8]:
```
print(f"Number of sentences in training data:␣
↪{len(processed_train_dataframes)}")

print(f"Number of sentences in test data: {len(processed_test_dataframes)}")

print(f"Number of sentences in dev data: {len(processed_dev_dataframes)}")

train_total_tokens = sum(len(df) for df in processed_train_dataframes.values())
print(f"Total number of tokens in training data: {train_total_tokens}")

test_total_tokens = sum(len(df) for df in processed_test_dataframes.values())
print(f"Total number of tokens in test data: {test_total_tokens}")

dev_total_tokens = sum(len(df) for df in processed_dev_dataframes.values())
print(f"Total number of tokens in dev data: {dev_total_tokens}")

train_total_predicates = sum((df['PREDICATE'] != '_').sum() for df in␣
↪processed_train_dataframes.values())
train_avg_predicates = train_total_predicates / len(processed_train_dataframes)
print(f"Average number of predicates per sentence in training data:␣
↪{train_avg_predicates:.2f}")

test_total_predicates = sum((df['PREDICATE'] != '_').sum() for df in␣
↪processed_test_dataframes.values())
test_avg_predicates = test_total_predicates / len(processed_test_dataframes)
print(f"Average number of predicates per sentence in test data:␣
↪{test_avg_predicates:.2f}")

dev_total_predicates = sum((df['PREDICATE'] != '_').sum() for df in␣
↪processed_dev_dataframes.values())
dev_avg_predicates = dev_total_predicates / len(processed_dev_dataframes)
print(f"Average number of predicates per sentence in dev data:␣
↪{dev_avg_predicates:.2f}")
```

```
Number of sentences in training data: 37205
Number of sentences in test data: 4525
Number of sentences in dev data: 4705
Total number of tokens in training data: 931170
```

```
Total number of tokens in test data: 94434
Total number of tokens in dev data: 97909
Average number of predicates per sentence in training data: 1.00
Average number of predicates per sentence in test data: 1.00
Average number of predicates per sentence in dev data: 1.00
```

1.4 Feature extraction

1.4.1 Feature 1: Compulsory feature

"This is a complex feature integrating: the directed dependency path from the token to the predicate + the predicate's lemma": Cannot use information from the dataset must assume that it works given any tokenized sentence and the predicate position.

[9]:
```
#from SpacyParsing.ipynb tutorial
logger = logging.getLogger("spacy")  # get logger for spacy
logger.setLevel(logging.ERROR)  # set logger level to error
os.environ['TRANSFORMERS_NO_ADVISORY_WARNINGS'] = 'true'  # suppress␣
 ↪transformers advisory warnings
#taken from notebook tutorial February 6
# python3 -m spacy download en_core_web_md
nlp = spacy.load("en_core_web_md")  # load spacy model en_core_web_md
```

Prepare functions to get complex feature

This feature is our complex/compulsory feature that gives us a dependency path from each token to the predicate with up and down arrows along with the predicate lemma.

This is a significant feature for the model as it captures the syntactic relationship between each token and the predicate, encouraging accurate semantic role labeling. The syntactic path between a predicate and its arguments strongly indicates their semantic roles - tokens with similar dependency paths to the predicate will serve similar semantic functions. We add the predicate lemma because different predicates assign semantic roles differently, even with identical syntactic paths.

To achieve this we will need to find the paths to the root from each token and the predicate, find the lowest common ancestor of the token and the predicate, and then create the path from the token to the ancestor and from the ancestor to the predicate.

Pseudocode:

```
Features = []

For each token in the sentence:

    Find the dependency path from each token to the root.
    Find the dependency path from the predicate to the root.

    Find the lowest common ancestor of the token and the predicate.

    If the ancestor is the root, then the path is the full path UP from the token to the root a
    If the ancestor is not the root, then the path is the path UP from the token to the ancesto
```

If the predicate is the ancestor, then the path DOWN is empty.

Add the path and the predicate lemma to the Features list.

[23]:
```
def get_complex_feature(tokenized_sentence, predicate_position):
    """
    Gets the dependency path from each token to the predicate using LCA (lowest␣
↪common ancestor) approach.
    Uses ↑ for going up the tree and ↓ for going down.
    """
    doc = nlp(Doc(nlp.vocab, words=tokenized_sentence)) # process the sentence␣
↪with spaCy

    target = doc[predicate_position] # the predicate token we want paths to
    target_lemma = target.lemma_ # get the lemma of the predicate token (used␣
↪to create feature)

    def find_path_to_root(token):  # Function to find path from token to root
        path = []
        current = token
        while current.head != current: # Continue until we reach the root (a␣
↪token that is its own head)
            path.append((current, current.dep_))
            current = current.head
        path.append((current, current.dep_))  # Add the root itself
        return path

    results = []

    for i, token in enumerate(doc): # For each token in the sentence
        if i == predicate_position: # If this is the predicate token itself
            results.append(f"self | {target_lemma}")
            continue

        token_to_root = find_path_to_root(token) # find the path from the token␣
↪to the root
        target_to_root = find_path_to_root(target) # find the path from the␣
↪predicate to the root

        token_indices = [t[0].i for t in token_to_root] # get the indices of␣
↪the tokens in the path
        target_indices = [t[0].i for t in target_to_root] # get the indices of␣
↪the predicate tokens in the path

        # Find the LCA (first common ancestor in both paths)
        #https://www.geeksforgeeks.org/lowest-common-ancestor-binary-tree-set-1/
        lca_found = False
```

```
        for i, token_idx in enumerate(token_indices):
            if token_idx in target_indices: #ancestor found (could be the root)
                j = target_indices.index(token_idx) #get the index of the␣
↪ancestor, will be 0 if ancestor is the predicate
                lca_found = True #set the flag to true

                path_up = [f"↑{t[1]}" for t in token_to_root[:i]] #path up from␣
↪token to ancestor, if ancestor is the root then the path is full (up and␣
↪down)

                path_down = [f"↓{t[1]}" for t in reversed(target_to_root[:j])]␣
↪#path down from ancestor to predicate, if ancestor is the predicate then the␣
↪path is empty

                final_path = "".join(path_up + path_down) #combine the paths
                results.append(f"{final_path} | {target_lemma}") #add the path␣
↪and predicate lemma to the results
                break
        if not lca_found:
            results.append(f"nopath | {target_lemma}") #if no path found then␣
↪add no path to the results (shouldnt happen due to root but may need to␣
↪debug spacy errors)

    return results
```

Test the functions

[24]:
```
tokenized_sentence = ["I", "broke", "the", "window", "with", "the", "panda",␣
 ↪"sticker"] #example sentence (tokenized)
predicate_position = 1 # 'broke' is the predicate
dependency_paths = get_complex_feature(tokenized_sentence, predicate_position)␣
 ↪#use function to get dependency paths
print(dependency_paths)
```

```
['↑nsubj | break', 'self | break', '↑det↑dobj | break', '↑dobj | break', '↑prep
| break', '↑det↑pobj↑prep | break', '↑compound↑pobj↑prep | break', '↑pobj↑prep |
break']
```

1.4.2 Feature 2: Lemma

Token lemma

This feature complements our complex feature by focusing on the semantic content of each token. While the dependency paths capture structural relationships, lemmas help the model recognize semantically similar arguments across different sentences, even when they appear in different syntactic contexts. For instance, terms like “vehicle”, “car”, and “truck” as lemmas would help the model identify similar semantic roles despite varying sentence structures.

```
[25]: def get_lemma_feature(tokenized_sentence):
    """
    Creates a feature using just the lemma (base form) of each token.
    """
    doc = nlp(Doc(nlp.vocab, words=tokenized_sentence))  # Process with spaCy␣
 ↪to get lemmas

    features = []
    for token in doc:
        features.append(token.lemma_)

    return features

tokenized_sentence = ["I", "broke", "the", "window", "with", "the", "panda",␣
 ↪"sticker"]
lemma_features = get_lemma_feature(tokenized_sentence)
print(lemma_features)
```

```
['I', 'break', 'the', 'window', 'with', 'the', 'panda', 'sticker']
```

1.4.3 Feature 3: POS Tag

pos tag

Part-of-speech tags provide grammatical category information that complements both our syntactic path and lemma features. POS tags help identify potential semantic roles independent of specific word choices - for example, nouns often serve as arguments while adjectives typically don't and proper nouns (PROPN) frequently function as agents.

```
[26]: def get_pos_feature(tokenized_sentence):
    """
    Creates a feature using just the part-of-speech tag for each token.
    """
    doc = nlp(Doc(nlp.vocab, words=tokenized_sentence))

    features = []
    for token in doc:
        features.append(token.pos_)

    return features

tokenized_sentence = ["I", "broke", "the", "window", "with", "the", "panda",␣
 ↪"sticker"]
pos_features = get_pos_feature(tokenized_sentence)
print(pos_features)
```

```
['PRON', 'VERB', 'DET', 'NOUN', 'ADP', 'DET', 'NOUN', 'NOUN']
```

1.5 Prepare features and labels for logistic regression

For each sentence in the dataset we will create a list of tokens and the gold target (SRL label). We will then prepare the features using the previously defined functions. For every feature, token and label in each sentence we will then store in a bigger list representing the whole dataset.

We will then make the features one hot encoded and the labels encoded with LabelEncoder. The encoders must use only the training data to fit.

[27]:
```
class FeatureLabelPreparer:
    def __init__(self, dataframes):
        self.dataframes = dataframes

    def prepare_features_labels(self):
        """
        Prepare features and labels verbosely. Takes the target label␣
↪(argument) from dataframe and creates a list of features and labels.
        """
        feature1 = []  # initialize empty list to store features
        feature2 = []  # initialize empty list to store features
        feature3 = []  # initialize empty list to store features
        labels = []  # initialize empty list to store labels
        tokens_all = []  # initialize empty list to store tokens

        for sentence, df in tqdm(self.dataframes.items(), desc="Processing␣
↪sentences"):  # iterate over each sentence and its dataframe, tqdm shows␣
↪progress
            # if sentence[0] == 'O':  # check if the sentence starts with 'O'
            #     continue  # skip the sentence if it starts with 'O' (no␣
↪predicate)
            # else:
            tokens = []  # initialize empty list to store tokens of the current␣
↪sentence
            for index, row in df.iterrows():  # iterate over each row in the␣
↪dataframe
                if row['LABELS-P0'] == '_' or row['LABELS-P0'] == 'V' or␣
↪row['LABELS-P0'] == '':  # check the label in 'LABELS-P0' column
                    labels.append('O')  # target label is 'O' if predicate or␣
↪non argument
                else:
                    labels.append(row['LABELS-P0'])  # append the actual label␣
↪otherwise
                tokens.append(row['WORD'])  # append the word to the tokens list
                tokens_all.append(row['WORD']) # append the token to the tokens␣
↪list
            #get complex feature
            predicate_position = df[df['LABELS-P0'] == 'V'].index[0]  # find␣
↪the position of the predicate
```

```
            complex_features = get_complex_feature(tokens, predicate_position) # get dependency paths for the sentence
            for feature in complex_features:  # iterate over each token and its path
                feature1.append([feature])  # create complex feature and append to features

            lemma_features = get_lemma_feature(tokens)
            for feature in lemma_features:
                feature2.append([feature])
            pos_features = get_pos_feature(tokens)
            for feature in pos_features:
                feature3.append([feature])
            # if len(complex_features) != len(tokens) or len(lemma_features) != len(tokens) or len(pos_features) != len(tokens):
            #     print(f"Sentence: {sentence, len(complex_features), len(lemma_features), len(pos_features), len(tokens)}")
            #     print(f"Complex features: {complex_features}")
            #     print(f"Lemma features: {lemma_features}")
            #     print(f"POS features: {pos_features}")
            #     print(f"Tokens: {tokens}")

            #     break
        return feature1, feature2, feature3, labels, tokens_all  # return the lists of features and labels

    def prepare_encoders(self, feature1, feature2, feature3, labels):
        """
        Prepares one hot encoding model for features and labels.
        """
        one_hot_encoder_feature1 = OneHotEncoder(handle_unknown='ignore')
        one_hot_encoder_feature2 = OneHotEncoder(handle_unknown='ignore')
        one_hot_encoder_feature3 = OneHotEncoder(handle_unknown='ignore')
        label_encoder = LabelEncoder()

        one_hot_encoder_feature1.fit(feature1)  # fit the encoder for features
        one_hot_encoder_feature2.fit(feature2)  # fit the encoder for features
        one_hot_encoder_feature3.fit(feature3)  # fit the encoder for features
        label_encoder.fit(labels)  # fit the encoder for labels
        feature_encoders = [one_hot_encoder_feature1, one_hot_encoder_feature2, one_hot_encoder_feature3]
        return feature_encoders, label_encoder  # return the fitted encoders

    def transform_features_labels(self, feature1, feature2, feature3, labels, feature_encoders, label_encoder):
        """
```

```
        Transforms features and labels using one hot encoding model.
        """
        one_hot_encoded_feature1 = feature_encoders[0].transform(feature1)  #␣
↪transform features using encoder
        one_hot_encoded_feature2 = feature_encoders[1].transform(feature2)  #␣
↪transform features using encoder
        one_hot_encoded_feature3 = feature_encoders[2].transform(feature3)  #␣
↪transform features using encoder

        #deal with unseen labels
        processed_labels = []
        for label in labels:
            if label in label_encoder.classes_:
                processed_labels.append(label)
            else:
                processed_labels.append('O')

        encoded_labels = label_encoder.transform(processed_labels)  # transform␣
↪labels using label encoder
        encoded_features = hstack([one_hot_encoded_feature1,␣
↪one_hot_encoded_feature2, one_hot_encoded_feature3])
        return encoded_features, encoded_labels  # return combined features and␣
↪labels

    def train_model(self): #creates a new encoder for each feature and label␣
↪encoder
        feature1, feature2, feature3, labels, train_tokens = self.
↪prepare_features_labels()
        feature_encoders, label_encoder = self.prepare_encoders(feature1,␣
↪feature2, feature3, labels)
        train_encoded_features, train_encoded_labels = self.
↪transform_features_labels(feature1, feature2, feature3, labels,␣
↪feature_encoders, label_encoder)
        return train_encoded_features, train_encoded_labels, train_tokens,␣
↪feature_encoders, label_encoder

    def test_model(self, feature_encoders, label_encoder): #uses existing␣
↪encoders to transform features and labels
        feature1, feature2, feature3, labels, tokens = self.
↪prepare_features_labels()
        encoded_features, encoded_labels = self.
↪transform_features_labels(feature1, feature2, feature3, labels,␣
↪feature_encoders, label_encoder)
        return encoded_features, encoded_labels, tokens
```

1.6 Scikit learn logistic regression

1.6.1 Training

[28]:
```
trainSet = FeatureLabelPreparer(processed_test_dataframes)
train_encoded_features, train_encoded_labels, train_tokens, feature_encoders,␣
↪label_encoder = trainSet.train_model()
```

```
Processing sentences: 100%|          | 4525/4525 [01:00<00:00, 74.41it/s]
```

[29]:
```
# logistic_regression_model = LogisticRegression(max_iter=1000)  # initialize␣
↪logistic regression model with max_iter=1000, which means the model will␣
↪perform a maximum of 1000 iterations to converge

#https://scikit-learn.org/stable/modules/generated/sklearn.linear_model.
↪LogisticRegression.html
logistic_regression_model = LogisticRegression(
    solver='saga',        # best for multi-class classification (scikit-learn␣
↪documentation)
    max_iter=2000,        # higher than default to ensure convergence
)
logistic_regression_model.fit(train_encoded_features, train_encoded_labels)  #␣
↪fit logistic regression model with features and class indices
```

[29]:
```
LogisticRegression(max_iter=2000, solver='saga')
```

[40]:
```
joblib.dump(logistic_regression_model, 'logistic_regression_model.pkl') # Save␣
↪the logistic regression model to a file
```

[40]:
```
['logistic_regression_model.pkl']
```

1.7 Test set

[30]:
```
testSet = FeatureLabelPreparer(processed_test_dataframes)
test_encoded_features, test_encoded_labels, test_tokens = testSet.
↪test_model(feature_encoders, label_encoder)
predicted_test_labels = logistic_regression_model.
↪predict(test_encoded_features)  # predict class indices using logistic␣
↪regression model
```

```
Processing sentences: 100%|          | 4525/4525 [01:01<00:00, 73.42it/s]
```

Make verbose gold and predicted labels, sort out None values in gold labels 'O'

[31]:
```
gold_labels_test = [label if label is not None else 'O' for label in␣
↪label_encoder.inverse_transform(test_encoded_labels)]
predicted_labels_test = [label if label is not None else 'O' for label in␣
↪label_encoder.inverse_transform(predicted_test_labels)]
```

Generate classification report

[32]:
```
classification_report_str = classification_report(gold_labels_test,␣
↪predicted_labels_test) # Generate a classification report

print("Classification Report:\n", classification_report_str)
```

```
Classification Report:
               precision    recall  f1-score   support

        ARG0       0.91      0.50      0.64      1680
        ARG1       0.89      0.52      0.66      3071
    ARG1-DSP       0.00      0.00      0.00         4
        ARG2       0.86      0.52      0.65      1031
        ARG3       1.00      0.11      0.20        71
        ARG4       0.79      0.47      0.59        55
        ARG5       0.00      0.00      0.00         1
        ARGA       0.00      0.00      0.00         1
    ARGM-ADJ       0.86      0.28      0.42       223
    ARGM-ADV       0.77      0.17      0.28       475
    ARGM-CAU       0.60      0.07      0.12        44
    ARGM-COM       0.00      0.00      0.00        13
    ARGM-CXN       0.00      0.00      0.00        12
    ARGM-DIR       0.75      0.06      0.12        47
    ARGM-DIS       0.88      0.28      0.42       175
    ARGM-EXT       1.00      0.17      0.28       103
    ARGM-GOL       0.00      0.00      0.00        24
    ARGM-LOC       0.79      0.07      0.14       202
    ARGM-LVB       1.00      0.13      0.23        69
    ARGM-MNR       1.00      0.08      0.14       144
    ARGM-MOD       0.99      0.62      0.76       427
    ARGM-NEG       0.98      0.53      0.69       208
    ARGM-PRD       0.00      0.00      0.00        44
    ARGM-PRP       0.75      0.04      0.08        74
    ARGM-PRR       0.95      0.29      0.45        68
    ARGM-TMP       0.91      0.29      0.44       516
      C-ARG0       0.00      0.00      0.00         3
      C-ARG1       1.00      0.10      0.18        51
  C-ARG1-DSP       0.00      0.00      0.00         1
      C-ARG2       0.00      0.00      0.00         7
      C-ARG3       0.00      0.00      0.00         2
  C-ARGM-CXN       0.00      0.00      0.00         5
  C-ARGM-LOC       0.00      0.00      0.00         1
         C-V       0.00      0.00      0.00        16
           O       0.95      1.00      0.97     85429
      R-ARG0       0.93      0.20      0.33        64
      R-ARG1       0.00      0.00      0.00        52
      R-ARG2       0.00      0.00      0.00         1
```

```
  R-ARGM-ADJ       0.00      0.00      0.00         1
  R-ARGM-ADV       0.00      0.00      0.00         1
  R-ARGM-DIR       0.00      0.00      0.00         1
  R-ARGM-LOC       1.00      0.11      0.20         9
  R-ARGM-MNR       1.00      1.00      1.00         6
  R-ARGM-TMP       0.00      0.00      0.00         2

    accuracy                           0.94     94434
   macro avg       0.49      0.17      0.23     94434
weighted avg       0.94      0.94      0.93     94434

/mnt/nvme0n1p1/elective/advanced-nlp/ass1/env/lib/python3.10/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/mnt/nvme0n1p1/elective/advanced-nlp/ass1/env/lib/python3.10/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
/mnt/nvme0n1p1/elective/advanced-nlp/ass1/env/lib/python3.10/site-
packages/sklearn/metrics/_classification.py:1565: UndefinedMetricWarning:
Precision is ill-defined and being set to 0.0 in labels with no predicted
samples. Use `zero_division` parameter to control this behavior.
  _warn_prf(average, modifier, f"{metric.capitalize()} is", len(result))
```

Confusion matrix

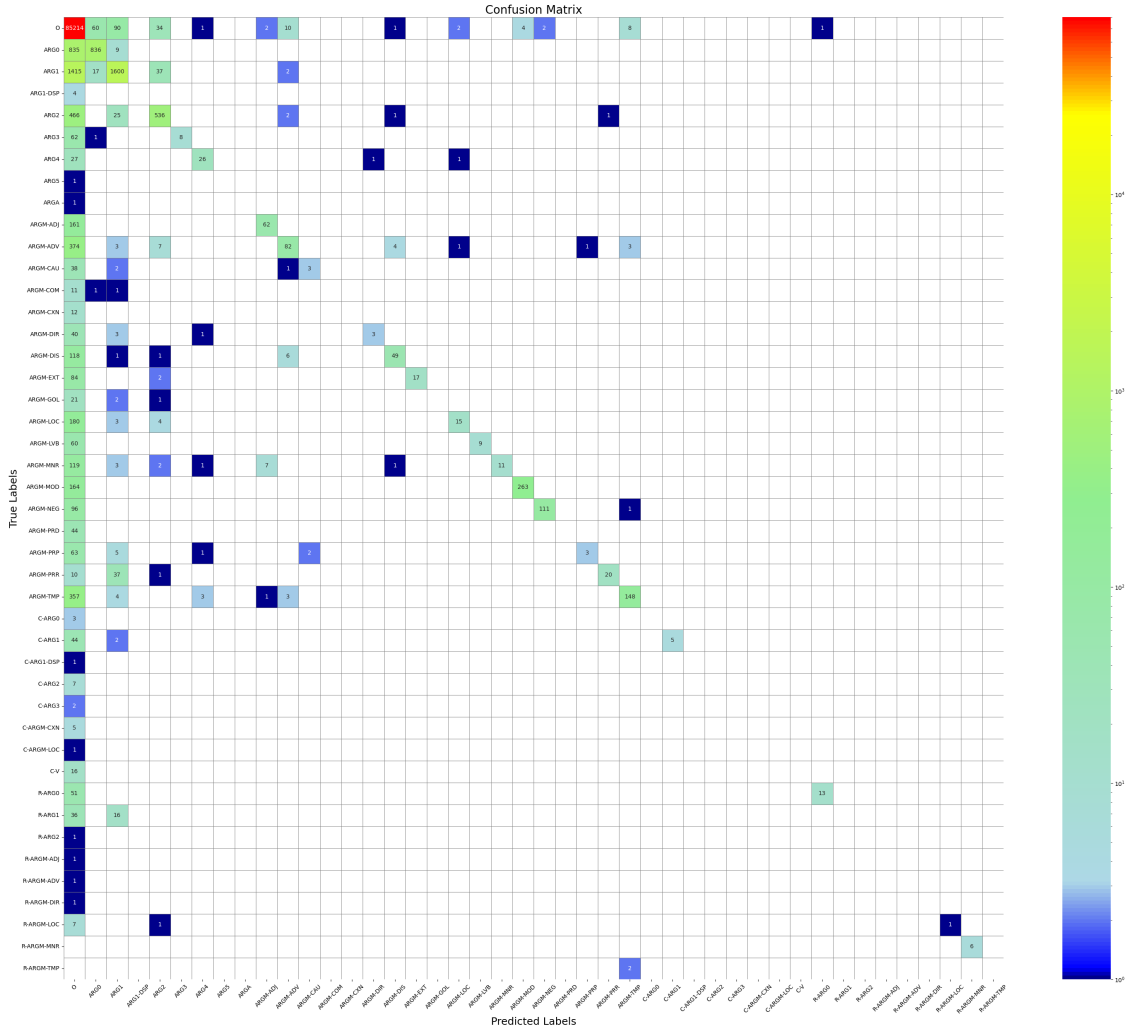
Using LogNorm to normalize confusion matrix values to make them more readable. This is because 'O' has an overwhelming number of values in the matrix, making it difficult to see the other values if linear.

[33]:

```python
categories = list(label_encoder.classes_)  # get class labels directly from the
 ↪LabelEncoder
# Handle None values without creating duplicates
if None in categories:
    # Remove None from categories
    categories.remove(None)
# Ensure 'O' is the first category
if 'O' in categories:
    categories.remove('O')
categories.insert(0, 'O')

conf_matrix = confusion_matrix(gold_labels_test, predicted_labels_test,
 ↪labels=categories)  # generate confusion matrix using gold and predicted
 ↪labels
```

```python
colors = [(0.0, "darkblue"), (0.01, "blue"), (0.1, "lightblue"), (0.5, "lightgreen"), (0.9, "yellow"), (1.0, "red")]  # define custom colormap with gradient from darkblue to red
custom_cmap = LinearSegmentedColormap.from_list("sharp_start", colors)  # create a colormap from the defined colors
plt.figure(figsize=(30, 25))  # set the figure size for the plot
sns.heatmap(conf_matrix, annot=True, fmt='d', cmap=custom_cmap, xticklabels=categories, yticklabels=categories, norm=LogNorm(vmin=1, vmax=80000), linewidths=0.5, linecolor='grey')  # plot heatmap with log normalization and grid lines
for i in range(len(categories)):  # iterate over categories to highlight specific values
    for j in range(len(categories)):  # iterate over categories for each row
        if conf_matrix[i, j] in [200, 2500, 80000]:  # check if the value is one of the specified values to highlight
            plt.text(j + 0.5, i + 0.5, conf_matrix[i, j], color='red', ha='center', va='center', fontsize=12, fontweight='bold')  # highlight the value in red
plt.xlabel('Predicted Labels', fontsize=18)  # set x-axis label with font size
plt.ylabel('True Labels', fontsize=18)  # set y-axis label with font size
plt.title('Confusion Matrix', fontsize=20)  # set the title of the plot with font size
plt.xticks(rotation=45)  # rotate x-axis labels for better readability
plt.tight_layout()  # adjust layout to prevent overlap
plt.show()  # display the plot
```



Save output of models predictions

[34]:
```python
output_df = pd.DataFrame({
    'Token': test_tokens,
    'Gold Label': gold_labels_test,
    'Predicted Label': predicted_labels_test
})
output_df.to_csv('test_predictions.csv', index=False)
```

1.8 Stand alone function

Input is tokenized sentence, predicate positions (binary list), model, feature encoders and label encoder. For multiple predicates in the sentence, the function will return a list of lists as cannot combine arguments for multiple predicates in the same list (as done in the original conll dataset). We will also readd the 'V' for predicate concerned.

[35]:

```
def standalone_function(tokenized_sentence, predicate_indicators, model,␣
↪feature_encoders, label_encoder):
    """
    This function takes a tokenized sentence and a list of predicate indicators␣
↪(0=not predicate, 1=predicate)
    and returns the predicate labels for all tokens for each predicate.
    """
    # Find all predicate positions from the indicators
    predicate_positions = [i for i, indicator in␣
↪enumerate(predicate_indicators) if indicator == 1]

    if not predicate_positions:
        return []  # No predicates found

    all_predictions = []

    for predicate_position in predicate_positions: #process each predicate
        # Feature 1: Complex feature
        complex_features = get_complex_feature(tokenized_sentence,␣
↪predicate_position)
        complex_features = [[feature] for feature in complex_features]

        # Feature 2: Lemma feature
        lemma_features = get_lemma_feature(tokenized_sentence)
        lemma_features = [[feature] for feature in lemma_features]

        # Feature 3: POS feature
        pos_features = get_pos_feature(tokenized_sentence)
        pos_features = [[feature] for feature in pos_features]

        # Transform features
        encoded_feature1 = feature_encoders[0].transform(complex_features)
        encoded_feature2 = feature_encoders[1].transform(lemma_features)
        encoded_feature3 = feature_encoders[2].transform(pos_features)
        features = hstack([encoded_feature1, encoded_feature2,␣
↪encoded_feature3])

        predicted_labels = model.predict(features) #predict labels for each␣
↪predicate
        predicted_labels = [label if label is not None else 'O' for label in␣
↪label_encoder.inverse_transform(predicted_labels)]

        predicted_labels[predicate_position] = 'V' # Add the predicate role␣
↪marker at the predicate position

        all_predictions.append(predicted_labels)
```

```
    return all_predictions
```

[37]:
```
tokenized_sentence = ["John", "bought", "a", "car", "and", "drove", "it", "to",␣
↪"work", "."]
predicate_indicators = [0, 1, 0, 0, 0, 1, 0, 0, 0, 0]
print(standalone_function(tokenized_sentence, predicate_indicators,␣
↪logistic_regression_model,  feature_encoders, label_encoder))
```

```
[['ARG0', 'V', 'O', 'ARG1', 'O', 'O', 'O', 'O', 'O', 'O'], ['O', 'O', 'O', 'O',
'O', 'V', 'O', 'O', 'O', 'O']]
```