CMSC 470 Final Project: Progress Report

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Project Overview

As a reminder, the goal of our project is to build an automatic crossword puzzle solver, trained on a data set of ~14,500 New York Times crosswords dating back to 1976.

The tentative name for the solver is **"Shortz Circuit"**.

Our progress so far includes

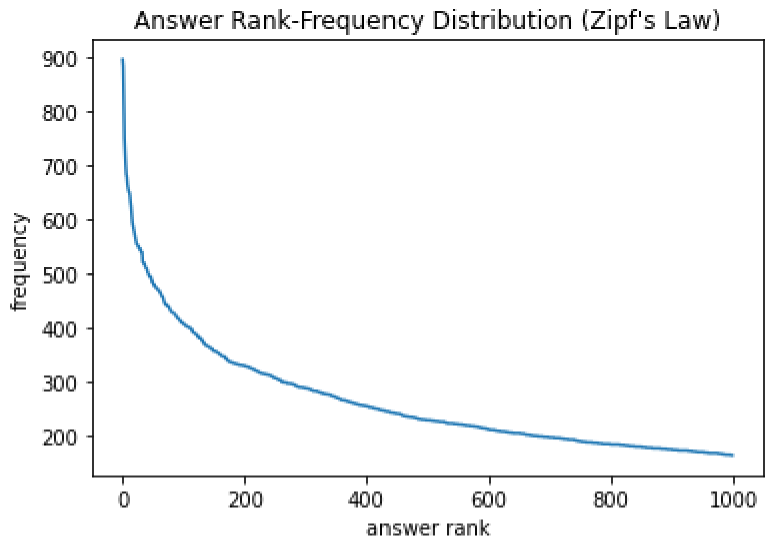
- some statistical analysis of the data set
- a working TF-IDF based guesser implementation
- a working Word2Vec based guesser implementation
- a clean framework for that includes the classes `Puzzle`, `Guesser`, and `Solver`
- two naive `Solver` implementations (that actually aren't half bad)

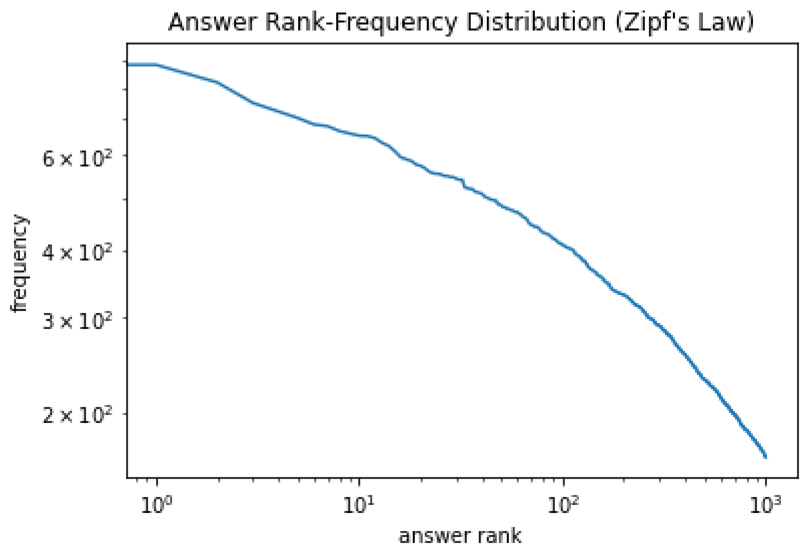
Data Set Statistics

- Puzzles Available: 14545
- Top 20 Most Common Answers:

```
[('AREA', 896),
('ERA', 883),
('ERIE', 819),
('ERE', 750),
('ALOE', 723),
('ONE', 703),
('ARIA', 684),
('ORE', 679),
('ALE', 665),
('ANTE', 658),
('EDEN', 652),
('ATE', 651),
('ELI', 645),
('ENE', 632),
('ELSE', 624),
('ARE', 610),
('ETA', 595),
('ERR', 589),
('ALI', 585),
('SPA', 576)]
```

- Does Zipf's Law Apply? Yup.





- What proportion of the answers are English n-grams?

```
def is_english_ngram(string, n):
    if n == "":
        return False
    elif n == 1:
        return string in ENGLISH_WORDS

    for i in range(1, len(string) - 1):
        head, tail = string[:i], string[i:]
        if is_english_ngram(head, 1) and is_english_ngram(tail, n-1):
              return True

    return False


total_clues = sum(answer_freqs.values())
ngram_counts = [0] * 3

for a in answer_freqs:
    for n in range(1, 4):
```

```
        if is_english_ngram(a, n):
            ngram_counts[n-1] += answer_freqs[a]
            break

for n in range(1, 4):
    print(f"Percentage of answers that are english {n}-grams:
{ngram_counts[n-1]/total_clues:0.3%}")

print(f"Total: {sum(ngram_counts)/total_clues:0.3%}")
```

```
Percentage of answers that are english 1-grams: 56.006%
Percentage of answers that are english 2-grams: 23.864%
Percentage of answers that are english 3-grams: 6.830%
```

Guesser Implementations

The `guess` function should take as input the clue and the current contents of the slot and then generate a set of guesses which fit the slot and each have an associated confidence score. Our current implementation uses vanilla TF-IDF trained on a huge number of clues (602,694).

When given a test clue, we find the `k` clues that are most similar (experimenting with both cosine similarity and L2-norm) and then filter for those that are compatible with the slot. Then, we use the similarity scores combined with the presence of repeats to calculate confidence scores. This looks like (from a `Guesser` class):

```
@staticmethod
def distance_to_confidence(dist):
    """map a clue embedding vector distance to a confidence value"""
    return 0.5 * math.e ** (-dist)

@lru_cache(maxsize=10**3)
def guess(self, clue: str, slot: str, max_guesses: int=5) -> List[Tuple[str,
float]]:
    clue_vector = self.vectorizer.transform([clue])

    # if clue vector is all 0's, we have never seen any of the words in the clue
before
    # so we cannot even try to make a guess (yet)
    if clue_vector[0].nnz == 0:
        # TODO: default to n-gram search or something
        return []

    distances, indices = self.model.kneighbors(clue_vector, n_neighbors=20)
    raw_guesses = [self.answers_train[i] for i in indices[0]]

    def valid(g):
        o = True
        if len(slot):
            o &= len(g) == len(slot)
```

```
        o &= g.lower() not in clue.lower()
        return o

    # convert distances to confidences
    guesses = [
        (g, self.distance_to_confidence(d))
        for g, d in zip(raw_guesses, distances[0]) if valid(g)
    ]

    # if a guess appears multiple times, interpret confidences as independent
probabilities and combine
    unique_guesses = set(g for g, _ in guesses)
    guesses_combined = [
        (g, 1 - math.prod(1-conf for g_, conf in guesses if g_==g))
        for g in unique_guesses
    ]

    return list(sorted(guesses_combined, key=lambda item: item[1], reverse=True))
```

Crossword puzzles love to repeat clue-answer pairs so this approach actually works pretty well. On our test set, the correct answer appeared in the top 5 best guesses ~60% of the time.

Word2Vec Guesser Attempt

Motivation

Word2Vec is a useful tool in NLP which maps each word to a vector-based on its association with the documents. It is good at detecting the 'similarity' between different words as two similar words would result in two similar vectors in the n-dimensional vector space and vice versa. We initially believe this would be a good implementation of guesser as the clues are comprised of short sentences with fewer words than the quizzes we have learned throughout the semester. In theory, Word2Vec would be good at matching two similar clues together by calculating the closeness (cosine similarity) between 2 vectors.

Gensim is a library containing a good implementation of Word2Vec trainer and various pre-trained models. We used modules from this library to train and test the Word2Vec guesser. As a clue has multiple words, we applied an average function `avg_feature_vector` on each clue to obtain the vector representation of each clue. The vectors could also be clustered using KNearestNeighbors method and the `guess` function utilizes this property to obtain the nearest n guesses fast.

The following code defines the W2VGuesser class(Initializer, training, some utility functions are omitted to make the report concise):

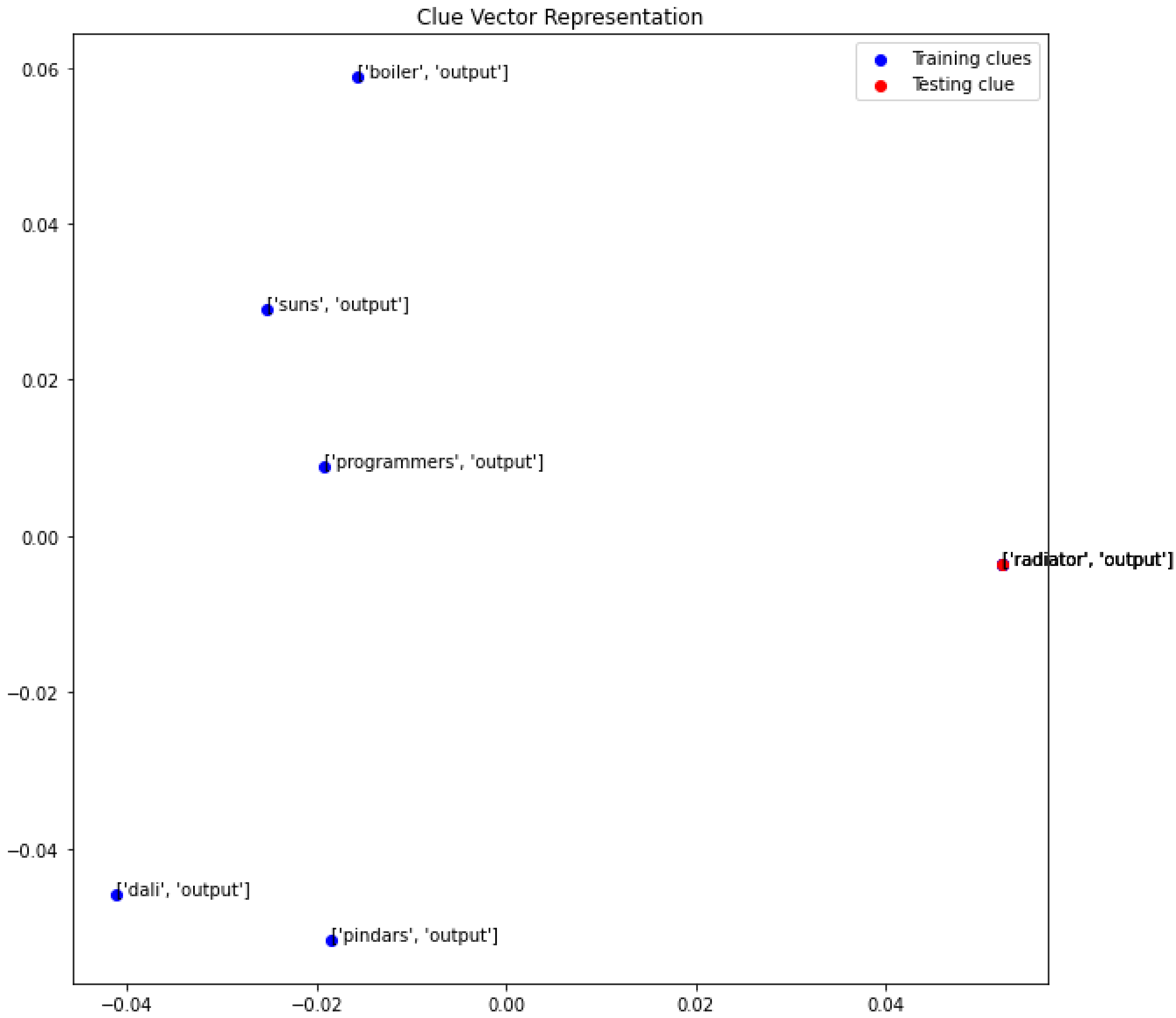
```
class W2VGuesser:
    # function average word2vec vector
    def avg_feature_vector(words, model, num_features, ind2key_set):
        feature_vec = np.zeros((num_features, ), dtype='float32')
        n_words = 0
        for word in words:
            if word in ind2key_set:
```

```
                n_words += 1
                feature_vec = np.add(feature_vec, model[word])
        if (n_words > 0):
            feature_vec = np.divide(feature_vec, n_words)
        return feature_vec

    # define cosine similarity score
    def sim_score(v1,v2):
        return 1 - spatial.distance.cosine(v1, v2)

    def guess(self, clue: str, slot: str, max_guesses: int=5) -> List[Tuple[str,
float]]:
        clue = clue.replace('\'', '')
        clue = clue.replace('"', '')
        clue = clue.replace(':', '')
        clue_vector =
self.word2vec_vectorizer([clue],self.model,self.dim,set(self.model.index_to_key))
        distances, indices =
self.nn_model.kneighbors(clue_vector,n_neighbors=max_guesses)
        raw_guesses = [self.answers[i] for i in indices[0]]

        def valid(g):
            o = True
            o &= len(g) == len(slot)
            o &= g.lower() not in clue.lower()
            return o

        # convert distances to confidences
        guesses = [
            (g, self.distance_to_confidence(d))
            for g, d in zip(raw_guesses, distances[0]) if valid(g)
        ]

        # if a guess appears multiple times, interpret confidences as independent
probabilities and combine
        unique_guesses = set(g for g, _ in guesses)
        guesses_combined = [
            (g, 1 - math.prod(1-conf for g_, conf in guesses if g_==g))
            for g in unique_guesses
        ]

        return list(sorted(guesses_combined, key=lambda item: item[1],
reverse=True))
```

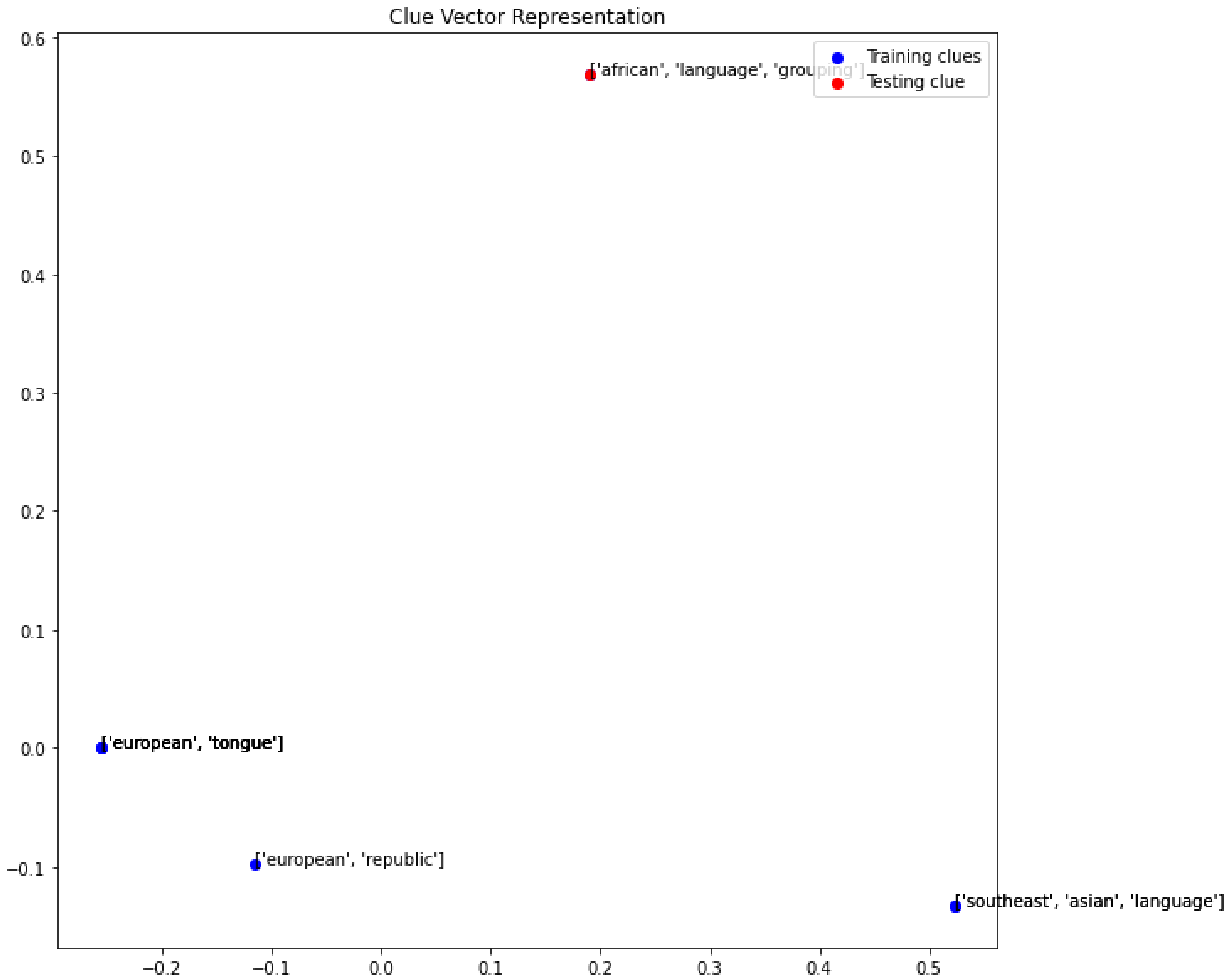
Visualization

As word vectors lives in n-dimensional vector space, it is possible to project each vector onto 2-dimensional plane to observe the closeness between different vectorized clues. To project a vector of higher dimension to a lower dimension space, one common method is Principal Component Analysis (PCA). PCA employs Singular

Value Decomposition (SVD) to extract the m-dimensional data from n-dimensional data(n$\geq$m) by preserving data corresponding to m-largest singular values.



In this example where the testing clue was 'radiator output', the Word2Vec guesser successfully distinguished the training data that matched to the clue (labeled red) with other confusing puzzles(blue) that also include the word 'output'. We can see under the PCA the correct clue vector is not aligned with the incorrect ones on the x-axis.



While the Word2Vec guesser may be effective at distinguishing the wrong ones, in some other cases it was not able to find the correct one. This example above illustrates that despite the guesser separating ‘African language group’ from other culture-language related confusing clues it did not find any correct vector close to the testing clue.

The result of this attempt, however, was less than ideal. The Word2Vec implementation of guesser only achieved an accuracy of roughly 45% compared to what we had for 55% in the baseline guesser. It is possible that in the crossword puzzle, the same answer was asked in completely different way resulting in the vector being far from each other.

Framework

The `Puzzle` makes it really easy to interact with a crossword puzzle, which is nontrivial since the slot-identifier scheme is idiosyncratic. There are also lots of helper functions for visualizing a puzzle in the terminal while it is being solved.

```
 P A T T I █ R I F F █ A S E A
 A V I A N █ D A L Y █ P A T S
 C O N S E R V A T I O N I S T
 __________ ██ M I R E ██
 M O E ██ T O S S █ O N A I R
```

```
ANDIE██AWED█URI
███PILSNER█ULAN
█______________█
PIED█________███
AMT█BAAS██CEDAR
BAGEL█ACRO██SAD
██BARN██SERRATE

______________
PROP█OBOE█STEED
ODES█NIPS█TEDDY
```

We use double-wide unicode chars to make it print out a bit nicer. It is also color coded if your terminal supports the proper ANSI escape codes:

The `Guesser` and `Solver` classes encapsulate the necessary functionality including loading the model(s) from disk. A `Guesser` implements a `guess` function with the following signature:

```
@lru_cache(maxsize=10**3)
def guess(self, clue: str, slot: str, max_guesses: int=5) -> List[Tuple[str, float]]:
    """Get a list of guesses represented as `(guess, confidence)` pairs (sorted best to worst)"""
```

Solution Attempts

A completely naive solution:

```
class BasicSolver(Solver):
    """
    The most obvious possible strategy:
```

```
    Iterate over the slots in order, writing (in ink) our best guess that is
compatible with the current contents of the slot
    Repeat until either grid is filled or we get stuck

    Uses the `BasicGuesser`
    """

    guesser_class: Type[Guesser] = BasicGuesser

    def solve(self, puzzle: Puzzle) -> bool:
        stuck = False
        while not puzzle.grid_filled() and not stuck:
            stuck = True
            for ident in puzzle.get_identifiers():
                current_slot = puzzle.read_slot(ident)
                if " " not in current_slot: continue

                clue = puzzle.get_clue(ident)
                gs = self.guesser.guess(clue, puzzle.read_slot(ident),
max_guesses=5)

                for g, conf in gs:
                    if compatible(current_slot, g):
                        puzzle.write_slot(ident, g)
                        stuck = False
                        break

        return not stuck
```

A slightly less naive solution:

```
class BasicSolverThreshold(Solver):
    """
    A variant of `BasicSolver`:

    Only fill in a slot if the guess confidence is above a threshold, which
decreases over with time.

    Run until threshold hits a minimum degeneracy point (say, 5% confidence)
    """

    guesser_class: Type[Guesser] = BasicGuesser

    def solve(self, puzzle: Puzzle) -> bool:
        threshold = 0.75    # on the first pass, only fill in those that we are
quite confident in

        while not puzzle.grid_filled() and threshold >= 0.05:
            stuck = True
            for ident in puzzle.get_identifiers():
                current_slot = puzzle.read_slot(ident)
```

```
                if " " not in current_slot: continue

                clue = puzzle.get_clue(ident)
                gs = self.guesser.guess(clue, puzzle.read_slot(ident),
max_guesses=5)

                for g, conf in gs:
                    if compatible(current_slot, g) and conf >= threshold:
                        puzzle.write_slot(ident, g)
                        stuck = False
                        break

            threshold *= 0.5    # exponential decay

        return not stuck
```

Both of these have the highly restrictive property that they solve the puzzle "in ink" so to speak, meaning that once a slot is written to it is never changed. Despite being really dumb, they actually work alright. I would even wager that `BasicSolverThreshold` does better on some Thursdays than I do!

Here are some performance metrics for a test suite of 100 randomly chosen puzzles (care was taken to separate train and test sets).

```
{'average_fill_accuracy': 0.513,
 'average_fill_percentage': 0.793,
 'solver': <class 'solvers.BasicSolver'>}
{'average_fill_accuracy': 0.606,
 'average_fill_percentage': 0.745,
 'solver': <class 'solvers.BasicSolverThreshold'>}
```

`average_fill_accuracy` represents the percentage of filled cells that were correct

`average_fill_percentage` represents the percentage of the grid that was filled at all (at present, these solvers leave a slot blank if they have never seen any of the words in the clue before)

What's Next?

- Improvements to the guesser: add n-gram search as an additional method of generating guesses
- Proper solver implementations (assign confidence heuristic to each cell as we go, beam search, etc.)