Joogle - CSI4107 Search Engine Project

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Foreword

The following is my report for the search engine project. Please note that rather than running my code, it is much easier to go to its website online at https://joogle-csi4107.herokuapp.com (https://joogle-csi4107.herokuapp.com). Instructions are in README.md.

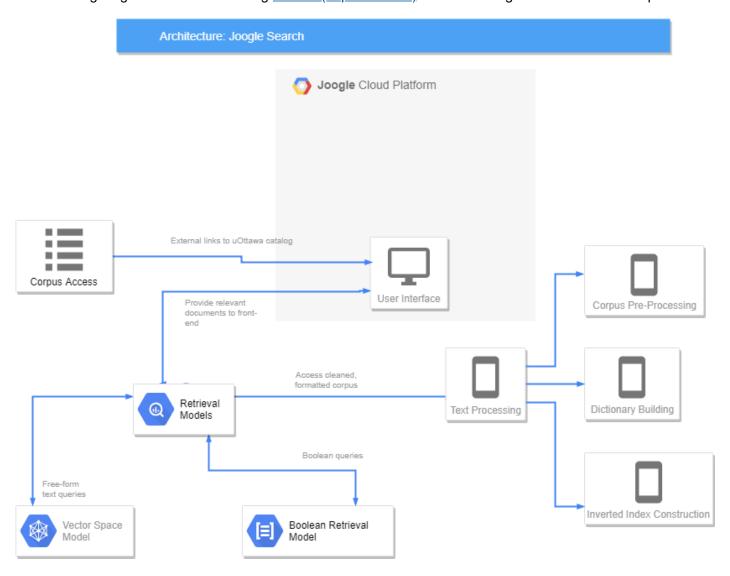
This report contains a system architecture diagram, followed by explanations and demonstrations of the modules implemented in my program, and concludes with the demonstration screenshots. The bulk of the length of this report is due to the explanations/demonstrations of the modules, so if these are unnecessary you may skip directly to <u>Demo</u> for the example queries suggested by Professor Barriere.

I recommend viewing the HTML version of this report, or viewing it on MBViewer
MBVIe

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System Architecture

The following diagram was created using draw.io (https://draw.io) and their Google Cloud Platform templates.



Modules - Mandatory

Corpus Pre-Processing

File(s)

uottawa_scrape.py

Description

This module scrapes and parses the uOttawa course catalogue using requests and beautifulsoup4, saving the data to data/catalogue-uottawa-ca.json (data/catalogue-uottawa-ca.json).

Demonstration

First, the HTML is acquired using the requests library, and a BeautifulSoup object is created.

```
In [1]: from uottawa_scrape import *
    html = scrape(to_file=False)
    print(html.find("div", {"class": "courseblock"}).text)
```

CSI 1306 Computing Concepts for Business (3 units)

Introduction to computer-based problem solving from the perspective of the bu siness world. Design of algorithms for solving business problems. Basics of c omputer programming in a modern programming language. Solving business proble ms using application packages including spreadsheets and databases. Basics of web design. Collaborative tools. Using open source software.Course Component: Laboratory, LectureThe courses ITI 1120, GNG 1106, CSI 1306, CSI 1308, CSI 13 90 cannot be combined for credits.

The HTML is then parsed using beautifulsoup4, such that it is stored in the following format.

```
In [2]: output = to_json(html, filename=None)
print(output[0])
```

{'id': 0, 'title': 'CSI 1306 Computing Concepts for Business (3 units)', 'bod y': 'Introduction to computer-based problem solving from the perspective of t he business world. Design of algorithms for solving business problems. Basics of computer programming in a modern programming language. Solving business problems using application packages including spreadsheets and databases. Basic s of web design. Collaborative tools. Using open source software.'}

This format facilitates easily manipulating and rendering the data using other modules.

User Interface

File(s)

- app.py
- templates/
 - static/
 - o css/
 - ∘ js/
 - img/
 - index.html
 - layouts.html
 - about.html
 - 404.html

Description

This module is implemented as a small Flask app. The UI is a parody of Google (see acknowledgements section below), allowing users to search the catalogue using either retrieval module.

Demonstration

See <u>Demo</u> below for a full demonstration.

Dictionary building

File(s)

- build dictionary.py
- construct index.py
- retrieval model.py

Description

This module contains utilities used to build the dictionary for the retrieval models. The actual construction of the dictionary takes place in retrieval model.py.

Demonstration

Note that due to the inclusion of the optional <u>phrase query indexing</u> module, said module is also a part of the dictionary building process. This will be expanded upon further in its own section below.

First, we reference the data created from the scraping model as seen above. We narrow the data to focus only on the descriptions (the titles were **not** made part of the dictionary).

```
In [3]: import json

data = json.load(open("data/catalogue-uottawa-ca.json"))
    descriptions = [row['body'] for row in data]
    descriptions[0]
```

Out[3]: 'Introduction to computer-based problem solving from the perspective of the b usiness world. Design of algorithms for solving business problems. Basics of computer programming in a modern programming language. Solving business problems using application packages including spreadsheets and databases. Basics of web design. Collaborative tools. Using open source software.'

These descriptions are then passed to the clean function from build_dictionary.py, which performs casing, normalization, lemmatization, stopword removal, and tokenization.

```
In [4]: from build_dictionary import clean
    print(clean(descriptions[0]))

    {'source', 'open', 'perspective', 'language', 'problem', 'programming', 'pack
    age', 'including', 'collaborative', 'computer', 'spreadsheet', 'based', 'soft
    ware', 'business', 'web', 'tool', 'modern', 'using', 'algorithm', 'design',
    'introduction', 'world', 'solving', 'application', 'database', 'basic'}
```

Inverted Index Construction

File(s)

construct_index.py

Description

Demonstration

The descriptions above are passed to the build_postings function, which returns both the index and the term dictionary. The index is constructed first, as follows:

```
In [5]: from construct_index import build_postings
    index, term_dict = build_postings(descriptions)
    print(index[0])

    (0, ['source', 'open', 'spreadsheet', 'perspective', 'language', 'problem',
    'package', 'programming', 'web', 'modern', 'database', 'problem', 'using', 'a
    lgorithm', 'including', 'collaborative', 'computer', 'design', 'introductio
    n', 'world', 'solving', 'tool', 'application', 'based', 'software', 'busines
    s', 'basic'])
```

Then, the term dictionary is constructed from the index. As it is, of course, a dictionary, retrieval is completed in **constant** $\mathcal{O}(1)$ time.

Its construction is completed in $\mathcal{O}(n\cdot(m+1))$ time, where m is the number of words in the longest document in the corpus. The n documents contained in the .json data are iterated over once to construct the index (as seen above) containing n rows. Then, each of the n rows of the index is to construct the term dictionary. At each row, m words are iterated over, incrementally updating its associated count. Pseudocode is presented below.

```
for (doc_id, words) in index:
    for word in words:
        term_dict[doc_id][word] += 1
```

The outer loop performs n iterations of m steps each for $O(n \cdot m)$ time. Combined with the n iterations of the index construction, we have $O(n+n\cdot m)=O(n\cdot (m+1))$ time.

Finally, both are returned.

Note: As an implementation decision, the weights are calculated later, in the VSM model itself. This simply made for a cleaner and more organized project structure. The weights could have been included here otherwise.

Corpus Access

File(s)

• same as in User Interface

Description

This module is implemented within the user interface, seen within the search results.

Demonstration

See Demo below for a full demonstration.

Boolean model of information retrieval

File(s)

brm.py

Description

The BRM (Boolean Retrieval Model) class operates as a model to query the corpus using boolean searches.

Demonstration

The boolean.py library is used for symbolic manipulation. The query is parsed as a logical expression, and then each literal word of the query is cleaned using the previous module.

```
In [7]: from brm import *
    b = BRM()
    q = "(computer OR systems) AND (data)"
    b.preprocess_query(q)
    wildcards: []
    computer OR systems AND data
Out[7]: OR(Symbol('computer'), AND(Symbol('systems'), Symbol('data')))
```

For each document, the truth value of each symbol is evaluated as the presence of the word in the document to resolve the expression. Each of the n documents are evaluated, for a query complexity of $\mathcal{O}(n)$.

As the BRM is unranked, the top_n argument will simply return the first n documents found and is only useful for demonstration purposes (as in this instance) or for the UI to paginate the results (not yet implemented).

```
In [8]: b.query(q, top_n=5)
      wildcards: []
      computer OR systems AND data
```

Out[8]:

	title	body
0	CSI 1306 Computing Concepts for Business (3 un	Introduction to computer-based problem solving
1	CSI 1308 Introduction to Computing Concepts (3	Introduction to computer based problem solving
2	CSI 1390 Introduction to Computers (3 units)	Computing and computers. Problem solving and a
3	CSI 2101 Discrete Structures (3 units)	Discrete structures as they apply to computer
21	CSI 4109 Introduction to Distributed Computing	Computational models. Communication complexity

Vector Space Model of information retrieval

File(s)

vsm.py

Description

The VSM (Vector Space Model) class operates as a model to query the corpus using tf - idf retrieval.

Demonstration

The t.f -idf scores are computed for each w_i , d_i pair upon construction of the model

Out[9]:

	0	1	2	3	4	5	6	7	8	9	 94	9
source	1.711807	0.000000	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000	0.0	 0.0	0.
open	1.711807	0.000000	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000	0.0	 0.0	0.
spreadsheet	2.012837	0.000000	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000	0.0	 0.0	0.
perspective	1.313867	0.000000	0.0	0.0	0.0	0.000000	0.0	0.0	0.000000	0.0	 0.0	0.
language	0.808717	0.808717	0.0	0.0	0.0	0.808717	0.0	0.0	0.808717	0.0	 0.0	0.

5 rows × 103 columns

At runtime, the query is pre-processed in the same fashion as the documents were processed orginally.

Only relevant documents are selected from the weight matrix. As the matrix is a 2-d array, this access takes place in $\mathcal{O}(w)$ time, where w is the number of words in the processed query, which is effectively constant $\mathcal{O}(1)$ time (assuming the user does not query every word in the vocabulary).

This is mathematically equivalent to performing an inner product on the weight matrix with one-hot vectors for each word, but it is clearly more space-efficient to simply slice the rows in question.

```
v.d_w.loc[:, q].T
In [11]:
Out[11]:
                                    2
                                        3
                                                  5
                                                      6
                                                           7
                                                                8
                                                                           94
                                                                                96
                                                                                     97
                                                                                          98
                                                                                              99 100 101
                                                                     9
                        0.0 0.0
                                 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
                                                              0.0 0.0
                                                                           0.0 | 0.0 | 0.0 | 0.0 | 0.0
            system
                                                                                                  0.0
                                                                                                        0.0
                                                                                                             (
            operating | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0
                                                                           0.0 0.0
                                                                                   0.0 0.0 0.0 0.0
                                                                                                        0.0
                                                                                                             (
           2 rows × 103 columns
```

The matrix is then summed along each column (corresponding to a document in the corpus), and sorted in descending order. This is then returned to our original data set and used to return the relevant documents to the user.

The "confidence" score is obtained by using the $\mathtt{tf}-\mathtt{idf}$ score through the sigmoid function (the s-curve), squishing all values between [0,1] with more extreme values on both ends. As of writing, this is not currently displayed to the user, but could be in the future.

In [13]: v.query("operating systems", top_n=10)

Out[13]:

	title	body	confidence		
id					
30	CSI 4139 Design of Secure Computer Systems (3	Security policies. Security mechanisms. Physic	0.929151		
12	CSI 3131 Operating Systems (3 units)	Principles of operating systems. Operating sys	0.929151		
90	CSI 5312 Distributed Operating Systems Enginee	Design issues of advanced multiprocessor distr	0.929151		
83	CSI 5175 Mobile Commerce Wireless networks support for m-commerce; m-co		0.879981		
91	CSI 5314 Object-Oriented Software Development	Issues in modeling and verifying quality and v	0.761868		
56	CSI 5134 Fault Tolerance (3 units)	Hardware and software techniques for fault tol	0.761868		
32	CSI 4141 Real Time Systems Design (3 units)	Definition of real-time systems; examples. C	0.761868		
89	CSI 5311 Distributed Databases and Transaction Principles involved in the design implemen		0.761868		
24	CSI 4124 Foundation of Modelling and Simulatio	The modelling and simulation process from a pr	0.761868		
35	CSI 5100 Data Integration (3 units)	Materialized and virtual approaches to integra	0.641406		

Modules - Optional

Phrase Query Indexing

File(s)

phrase indexing.py

Description

This module uses the Jaccard coefficient to identify phrases from a candidate set (identified as hyphenated words), as seen in class.

Demonstration

First, the candidate set is assembled as all hyphenated words in the corpus.

Then, bigrams of the corpus text are constructed, for calculation of Jaccard coefficients.

```
In [15]: corpus = [remove_punc(t.lower(), rm_hyphens=True) for t in descriptions]
    bigrams = make_bigrams(corpus)

    print(find_phrases(candidates, bigrams, threshold=0.7))

    {'entity-relationship': 1.0, 'one-way': 1.0, 'trap-door': 1.0, 'grey-box': 1.
    0, 'well-separated': 1.0, 'fail-safe': 1.0, 'locality-sensitive': 1.0, 'large -scale': 1.0}
```

Of course, the threshold can be tuned as well.

These phrases are then stored for later use in preprocessing the corpus and user queries.

Spelling Correction

File(s)

• spelling.py

Description

This module performs spelling corrections on user queries. However, as this is an extra module (working alone, I only have to implement one), I took some liberties with my implementation and elected to use a character-gram model instead of minimum edit distance (mostly out of curiosity).

Demonstration

First, as usual, the query is pre-processed (note: this happens slightly differently for the BRM).

Then, for each word in the query, if the word is not in the vocabulary, the spell check is applied. This is performed by computing the ratio of shared character-bigrams between the words. If the word is in the vocabulary, it is simply ignored (returned with 100% confidence). The word is also ignored if it is shorter than the minimum word len parameter, the default value of which is 4, or if it is in nltk.corpus.stopwords.words().

If the word ends in 's', and the word's singular form is in the vocabulary, then the word's singular form is returned. (Note: This is a potential argument for having used stemming over lemmatization. Feedback on this is welcome.)

Like minimum edit distance, then, it cannot correct words that are already spelled correctly; it is not context-aware.

As well, the threshold for which candidates are returned can be adjusted from its default value of 0.25. The low threshold reflects the choice of trigrams instead of bigrams as well as the fact that having at least one match is preferable to none at all (as the UI presently only takes the first match, though this will change in the future).

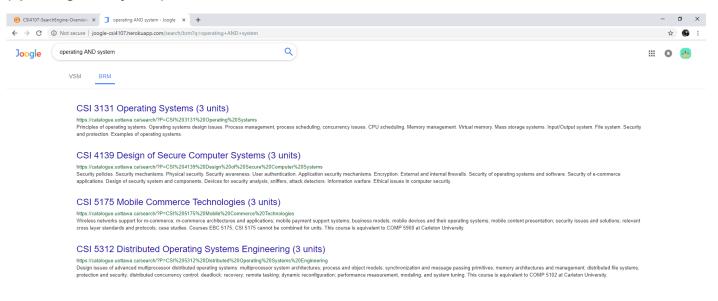
```
In [19]: print(spell_check("computional", b.build_vocab(), threshold=0.35))
        [('computational', 0.66666666666666666), ('computation', 0.5), ('computing', 0.45454545454545453), ('computer', 0.36363636363636363)]
```

Demo

The following demonstrations are reflective of the <u>live website (https://joogle-csi4107.herokuapp.com)</u> as of the date of submission.

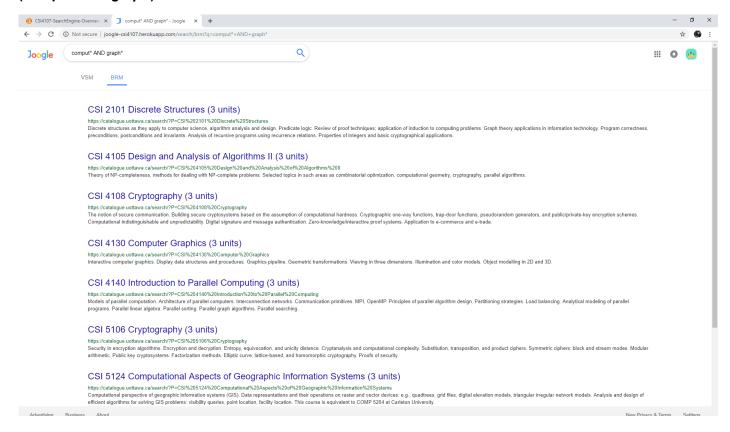
BRM

(operating AND system)

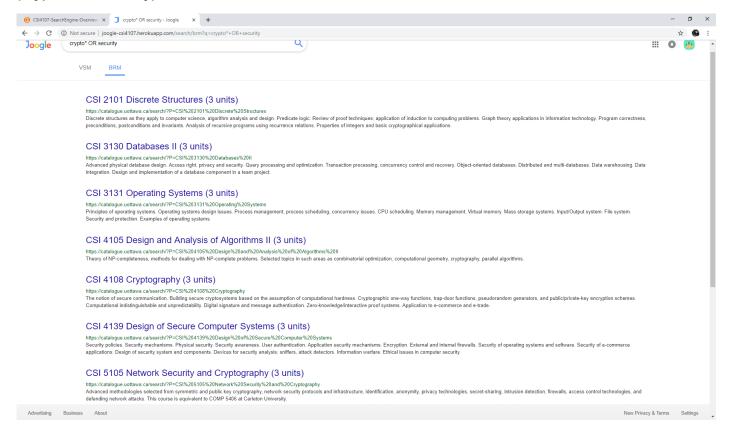


Advertising Business About New Privacy & Terms Settings

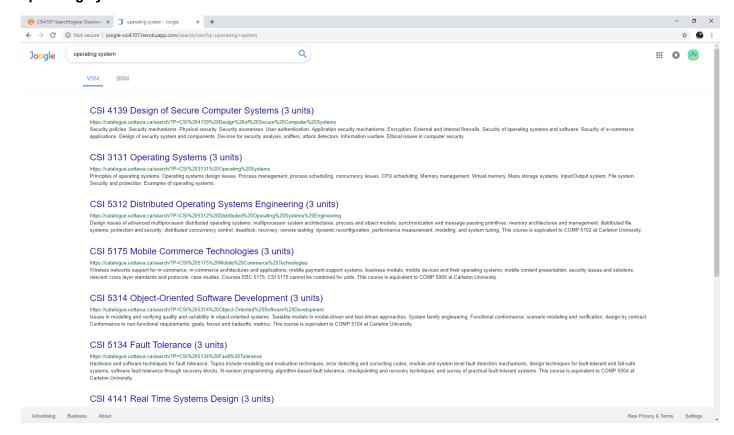
(comput AND graph)



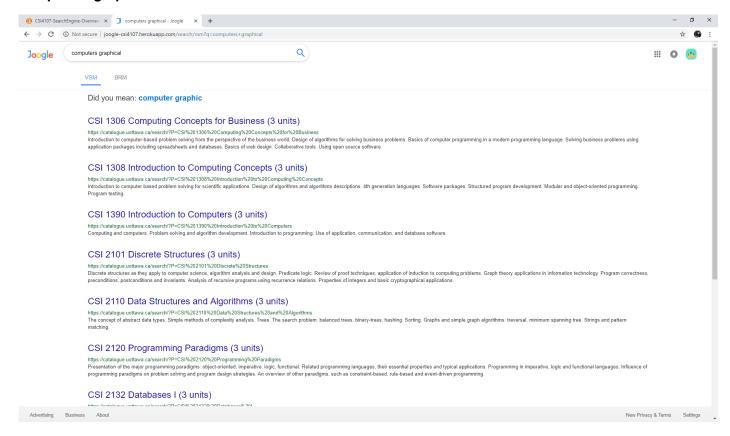
(crypto* OR security)



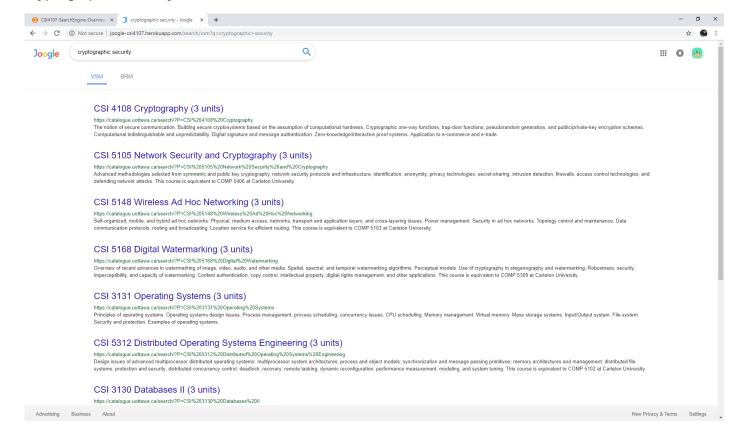
operating system



computers graphical



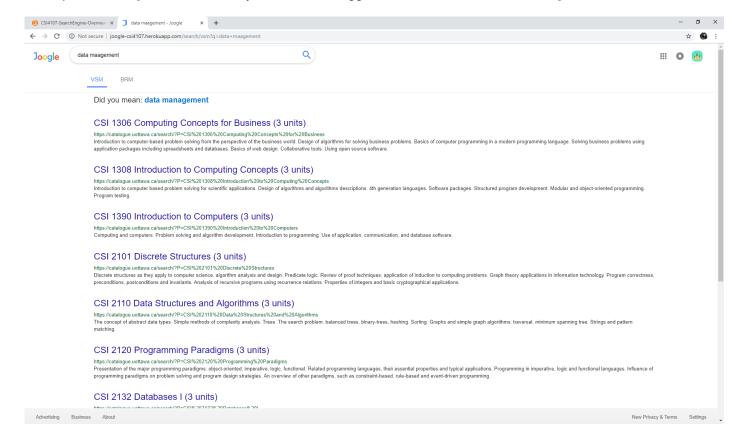
cryptographic security



Additional

data maagement

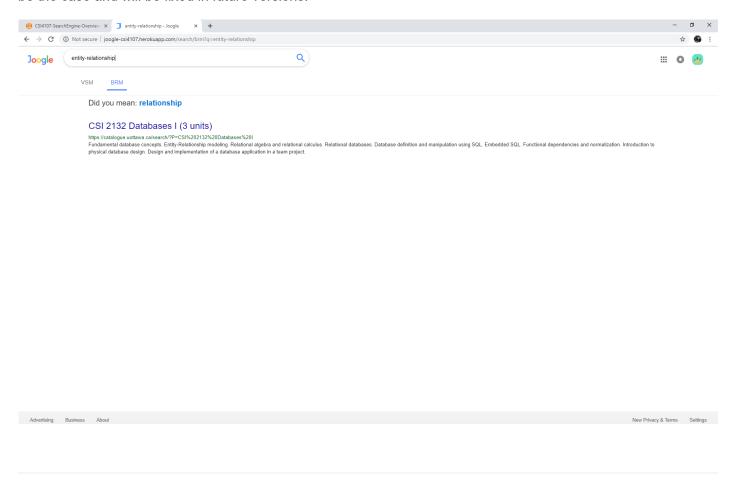
The first additional example showcases the implementation of the spell checking module (though it is also visible above). *Data maagement* is correctly revised and suggested to the user as *data management*.



entity-relationship

The second additional example showcases the implementation of phrase indexing. A search for entity-relationship would otherwise yield no results as *Entity-Relationship* would normally match neither (it would normally be stored as two separate words). However, the phrase is correctly indexed and matched in the boolean retrieval.

For some reason, the spell check fires here, despite the presence of the word in the vocabulary - this should not be the case and will be fixed in future versions.



Acknowledgements

First and foremost, most of the UI was inspired by/adapted from two sources. The index page was adapted from nicknish (https://codepen.io/nicknish/pen/cLbAg) on codepen.io, while the search result page was adapted from milynt (https://codepen.io/rmlynt/pen/AXkqJL). Rather than try to hide this by superficially changing things like variable names, I have left them primarily identical. However, all functionality (search, interactivity, infinite scrolling, etc.) is my own.

The logo was created <u>festisite (https://www.festisite.com/logo/google/)</u>, and edited using <u>lunapic (https://www110.lunapic.com/editor/)</u>.

As well, many code snippets from sources such as stack overflow have been referenced where appropriate throughout my code.