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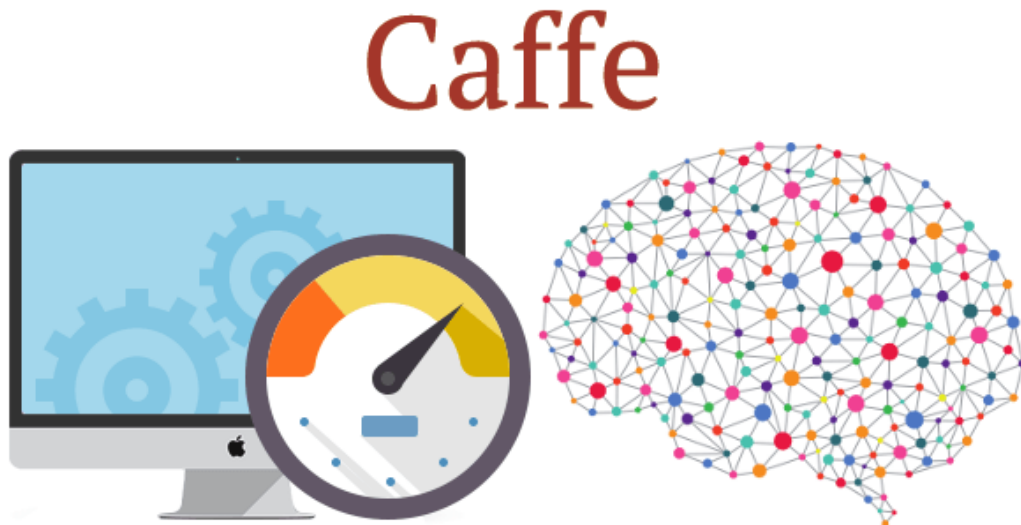
CS 4701: PRACTICUM IN ARTIFICIAL INTELLIGENCE

Food Recognition with Deep Learning

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1 Problem Description

Consider the problem of creating an artificially intelligent grocery shopper who is able to make recipe substitutions and suggestions based on availability. Such an agent would be highly desirable to anyone who would rather do something else with their time than shop for groceries, and the different intelligent components that go into this agent would have widespread applications in other fields.

Recent advances in machine learning algorithms and computing capabilities have enabled deep neural network architectures to surpass the state of the art traditional machine learning classifiers in nearly every problem domain. In particular, Convolutional Neural Networks have surpassed traditional computer vision and machine learning techniques in many tasks, provided with large amounts of data.

Inspired in part by the textbook grocery shopper example and in part by [IBM's work in recipe recommendation with Watson](#), we decided to build the perception system for food recognition, using deep learning methods in order to achieve the best possible performance. The ability to recognize a food item in an image has countless applications; for example, it is useful in building cooking robots, creating an artificially intelligent grocery shopper, automatically tracking shopper actions (i.e. Amazon Go), diet tracking programs, and many more.

2 High Level Design

2.1 Approach

Our first attempt to train our network on resulted in very poor ($< 5\%$) accuracy, so we decided to break the problem down into more manageable chunks.

We picked K Nearest Neighbors and Support Vector Machines as baseline classifiers so we would be able to meaningfully evaluate the Deep Convolutional Neural Network's performance. If we are using CNNs effectively, we should see much better results compared to the baseline. We used the LeNet network, as it is one of the most widely studied and well understood network architectures in the field, so we knew it would be fairly easy to work with.

We started with using the baseline classifiers to classify several types of hand drawn shapes with no feature extraction, mimicking the MNIST dataset. We simply used the grayscale pixel values of an image as the feature vector. We then trained the CNN on these, evaluated the performance, and compared the results.

2.2 Theory

2.2.1 K Nearest Neighbors

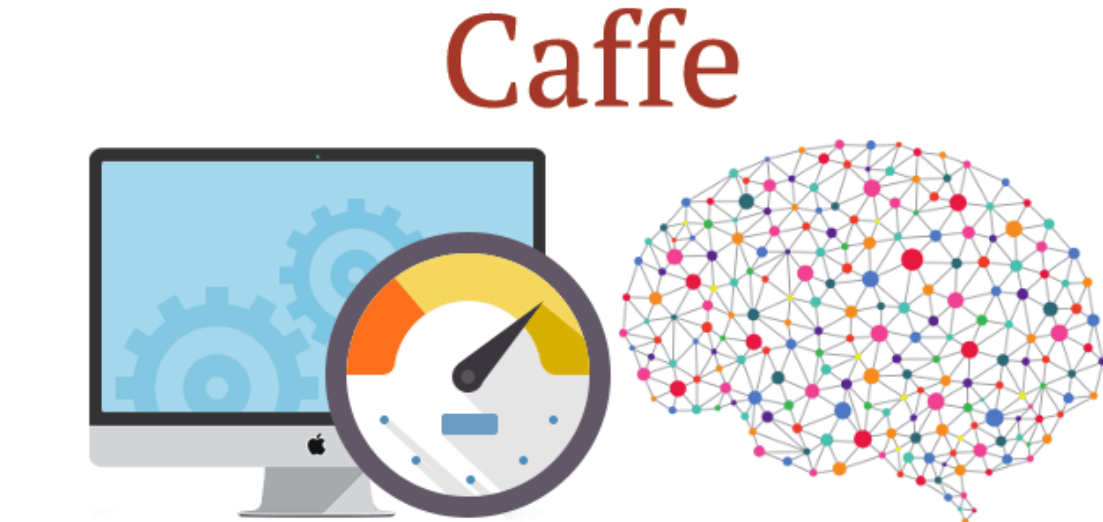
how does it work

2.2.2 Support Vector Machine

how does it work

2.2.3 Convolutional Neural Network (LeNet)

how does it work TODO LeNet architecture visualization



2.3 Software Architecture

2.3.1 potato.py

Loads model weights for a convolutional neural network and feeds forward test inputs through the network, evaluating its performance. The network we used was the off the shelf LeNet.

2.3.2 knn.py

Evaluates the K Nearest Neighbors classifier on test inputs. Experiments with thresholding and corner detection as feature extractors. We chose to implement this ourselves as we thought it would be a valuable exercise. However we did not implement other classifiers ourselves due to time constraints. TODO specify more

2.3.3 svm.py

Evaluates the Support Vector Machine classifier on test inputs. Uses the Scikit-Learn multiclass SVM.

3 Evaluation

For evaluating performance, we decided to focus on multiclass precision-recall curves, as they are a fairly holistic method of evaluating classifier performance, and the area under the curve is a simple metric to optimize.

We are not in a position where false positives or false negatives have different desirabilities, either, so no modification or special analyses are required.

3.1 Hand Drawn Data

3.1.1 K Nearest Neighbors

3.1.2 Support Vector Machine

3.1.3 Convolutional Neural Network

3.2 Food Dataset

3.2.1 K Nearest Neighbors

3.2.2 Support Vector Machine

3.2.3 Convolutional Neural Network

4 Conclusion

5 Future Work

6 Appendix

Here we present an annotated listing of all of the code we wrote for this project. The code is also available on [GitHub](#).

7 Permissions

Our code is under the Apache license; see [GitHub](#) for more details.

If you found our work helpful in your research, we would appreciate it if you could consider listing us as authors. Feel free to contact us.

8 Credits

Thanks to the Cornell Graphics and Vision lab for donating a tiny amount of GPU power for us to train our network. We did not have access to Nvidia GPUs, so we would have had to spend orders of magnitude more time training on CPUs otherwise.

Thanks to [gkielian](#) for the script we used to convert our PNG images into the custom binary format the LeNet expects.

References

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