**Task 4- ML vs AutoML**

**Manual Machine Learning:**

Machine learning (ML) has achieved considerable successes in recent years and an ever-growing number of disciplines rely on it. However, this success crucially relies on human machine learning experts to perform the following tasks:

* Preprocess and clean the data.
* Select and construct appropriate features.
* Select an appropriate model family.
* Optimize model hyperparameters.
* Postprocess machine learning models.
* Critically analyze the results obtained.

As the complexity of these tasks is often beyond non-ML-experts, the rapid growth of machine learning applications has created a demand for off-the-shelf machine learning methods that can be used easily and without expert knowledge

Automated Machine Learning provides methods and processes to make Machine Learning available for non-Machine Learning experts, to improve efficiency of Machine Learning and to accelerate research on Machine Learning.

**AutoML:**

Throughout recent years several off-the-shelf packages have been developed which provide automated machine learning. While there are more packages than the one listed below, we restrict ourselves to a subset of the most well-known ones:

* [**AutoWEKA**](http://www.cs.ubc.ca/labs/beta/Projects/autoweka/) is an approach for the simultaneous selection of a machine learning algorithm and its hyperparameters; combined with the [WEKA](http://www.cs.waikato.ac.nz/ml/weka/)package it automatically yields good models for a wide variety of data sets.
* [**Auto-sklearn**](http://automl.github.io/auto-sklearn/stable/) is an extension of AutoWEKA using the Python library [scikit-learn](http://scikit-learn.org/stable/) which is a drop-in replacement for regular scikit-learn classifiers and regressors.
* [**TPOT**](http://epistasislab.github.io/tpot/) is a data-science assistant which optimizes machine learning pipelines using genetic programming.
* [**H2O** AutoML](http://docs.h2o.ai/h2o/latest-stable/h2o-docs/automl.html) provides automated model selection and ensembling for the [H2O machine learning and data analytics platform](http://docs.h2o.ai/h2o/latest-stable/h2o-docs/welcome.html).
* [TransmogrifAI](https://github.com/salesforce/TransmogrifAI) is an AutoML library running on top of Spark.
* [**MLBoX**](https://github.com/AxeldeRomblay/MLBox) is an AutoML  library with three components: preprocessing, optimisation and prediction.

**ML Accessibility**

Backed by its solid performance and user-friendly design, AutoML greatly lowers the barrier to entry for many typical scenarios where ML might be applied. So far, Google has released [AutoML Vision](https://cloud.google.com/vision/" \t "_blank) for image analysis, AutoML Natural Language for unstructured text analysis, and AutoML Translation for dynamic translation between languages.

With AutoML vision, whether its binary classification or object recognition or anything in between, one only needs to upload a dozen or so sample images (or paragraphs of text) with labels onto a web portal to get started. AutoML equips businesses with the power of ML to solve certain types of traditionally difficult, high-value business problems without having to hire for expensive skill sets.

**Prototyping**

The astounding efficiency of AutoML can be extremely powerful to enable rapid, high-fidelity prototyping when building ML-enhanced user experiences. Instead of running a team of data scientists and spending months architecting and model tuning, product companies can now use AutoML to generate models that achieve near-optimal performances within as little as a few minutes. Combined with the ability to deploy quickly via REST API, product companies are now able to experiment with intelligent user experiences at a much faster pace and drive product innovation in exciting new angles.

**Reproducibility:**

AutomL can be reproduced any number of times with less piece of code and implementation which is not that easy with Manual ML.