**ML optimization of automated liquid handling parameters**

**Summary**

Materials Accelerated Platforms (MAPs) are an emerging paradigm for the discovery of materials that combine high-throughput experimentation, automation, and artificial intelligence in order to achieve autonomous experimentation1. Although there is many commercial equipment that can be used for the development of MAPs, the number of materials that can be processed are limited since most tools have not been designed for the automation of experiments that are specific for Materials Science2. For example, most liquid-handling robots for automated solution-based synthesis and processing of materials are engineered to pipette aqueous solutions and are not calibrated for the accurate transfer of viscous liquids. Although accurate handling parameters can be achieved for the transfer of viscous liquids, the process of obtaining these parameters is time consuming and must be performed by a human3. To make liquid-handling robots compatibility with autonomous experimentation more robust, new automated methods that calibrate the robots to handle liquids with a wider spectrum of viscosities is required.

This project aims to develop a ML learning algorithm that can drive the optimization of the liquid handling parameters of an OT2 pipetting robot for the accurate transfer of viscous liquids ranging from 10-104 cP. In particular, we will test different ML algorithms and tune their hyperparameters to find the model that given a previous data set selects the most likely liquid handling parameters that will lead to the least amount of transfer error and transfer time.

The proposed model work by training a ML learning algorithm (multi-linear regression or gaussian process) that generates a prediction of error based on the transfer parameters selected. This model is used as a surrogate model with Baysian Optimization (BO) algorithm that explores the parameter space and selects the most likely set of parameters that will lead to them minimization of the error. The values thrown by the BO will be used to transfer the liquid experimentally in a OT2 and the transfer error will be evaluated through a gravimetric method. The model will be updated with the latest set of conditions and it’s corresponding transfer error, and the optimization will be run again until the optimal conditions are found.

**Objectives**

1. Study effect of implementing the following ML models as surrogate models:
   1. Multilinear regression
   2. Gaussian process
2. Study effect of training model with a different amount of data using the following ML models as surrogate models:
   1. Multilinear regression
   2. Gaussian process
3. Study of effect of hyperparameter selection for the selection of best transfer parameters using BO:
   1. Acquisition function
      1. "LCB" for lower confidence bound.
      2. "EI" for negative expected improvement.
      3. "PI" for negative probability of improvement.
      4. "gp\_hedge" Probabilistically choose one of the above three acquisition functions at every iteration.

**Methods**

The optimization of the transfer parameters of previously calibrated viscous liquid standards will be performed as follows:

1. Use visc\_liquid\_measuremet\_v3a.py to generate a suggestion of next optimal dispensing values. The surrogate model will be based on a lin or gpr model trained with using the full manual calibration data set, half of the calibration data set, a quarter of the calibration data set and using only the first point of the calibration data set.
2. Input suggestions into the dictionary defined in .ipynet. Perform gravimetric method to obtain mass and transfer time during the experiment
3. Input values of mass and transfer time into visc\_liquid\_measuremet\_v3a.py.
4. Repeat a-c for a total of 15 times.
5. Plot the Iteration vs Error graph for ML guided and manual experimentation results.

The experiment described above has to be repeated using the lin and gpr surrogate models.

Chart, line chart

Description automatically generated

**References**

1 M. Seifrid, J. Hattrick-Simpers, A. Aspuru-Guzik, T. Kalil and S. Cranford, Matter, 2022 ,5, 1-5.

2 M. Christensen, L. P. E. Yunker, P. Shiri, T. Zepel, P. L. Prieto, S. Grunert, F. Bork and J. E. Hein, Chem. Sci., 2021, 12, 15473–15490.

3 How to handle viscous liquids in Protocol Designer, https://support.opentrons.com/s/article/How-to-handle-viscous-liquids-in-Protocol-Designer, (accessed January 23, 2023).