## Analysis v3 - A new data analysis concept

## General concept

Conceptually, this analysis framework consists of an analysis pipeline containing several data processing nodes as illustrated in Fig. 1. The nodes can be either functions or classes (see for example the module data\_processing.py). Several conceptual processing pipelines can be defined and run on the same input raw data, or a subset of it, specified by channel names. For example, as shown in Fig. 1, if the raw data consists of single shots acquired on several readout channels, we could create Pipeline 1 (green) for each readout channel, or analyze only channel 0 according to Pipeline 2 (blue) and then Pipeline 3 (purple) in order to quantify the differenced between ignoring and including the f-level in the classification of states (second node).

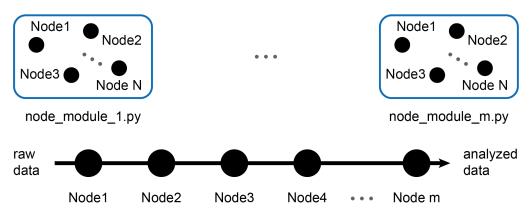
The class PipelineDataAnalysis defined in the module pipeline\_analysis.py extracts raw data and handles the parsing of a single pipeline. The pipeline can be either passed in when this class is initialized via the options\_dict dictionary with the key processing\_pipe, or it can be defined in the experimental metadata, which this class extracts from the data file. PipelineDataAnalysis creates the dictionary data\_dict, where it puts the experimental metadata and the raw data it extracts. The data\_dict is passed from node to node in the pipeline, and each node saves the processed data into this dictionary with a unique key, specified in the input parameter keys\_out.

All the nodes process data from data\_dict specified by the keys in the input parameter keys\_in. Hence, in practice one does not need to write individual processing\_pipes for each readout channel in the data. All the nodes for all the channels can be concatenated into a long pipeline, where ones specifies in keys\_in which channel(s) the node to process. For example, the following pipelines are all valid:

- $\bullet$  processing\_pipe = filter resets ch0 filter resets ch1 ... filter resets ch N Rabi on filtered ch0 Rabi on filtered ch1 ... Rabi on filtered ch N
- processing\_pipe = filter reset ch0 classify qubit ch0 classify qutrit ch0 Rabi on output of classify qubit Rabi on output of classify qutrit
- $\bullet$  processing\_pipe = average ch0 ... average ch N get stderr ch0 ... get stderr ch N plot averaged ch N single qubit RB on averaged ch0 ... single qubit RB on averaged ch N-1

At the moment, analysis\_v3 has support only for 1D data, and one needs to define a different pipeline for each measurement object,

Several modules containing several processing functions (nodes)



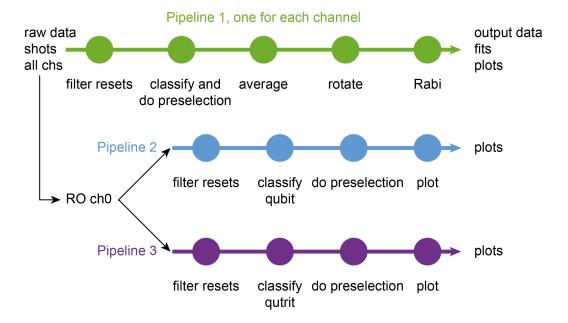


Figure 1: Overview of analysis\_v3. The last 3 colored pipelines are examples of how some raw single shot data can be processed in different ways.

i.e. there are currently no nodes that handle multiple measurement objects. The measurement object can be a qubit, a TWPA, a device, etc.; it is the object which is being characterized. Both of these limitations need to be addressed in the future. At this point, it is not clear how to deal with 2D data, or multi-object measurements where the analysis needs to take into account joint information.

If a measurement object is used in the pipeline, the analysis will most

likely require that cal\_points, sweep\_points, meas\_obj\_sweep\_points\_map, and meas\_obj\_value\_names\_map exist in the metadata. If they are missing in the metadata from the HDF5 files, you can still pass in a dictionary with the missing key-value pairs in the options\_dict with the key exp\_metadata. This dictionary will be appended to the metadata dictionary extracted from the data file. This requirement already raises some issues in some cases because the framework assumes the variables just mentioned are necessarily defined for the measurement object. Already we ran into issues when using the classifier detector with correlated == True. In this case the detector creates an additional data column for the correlated data with the value name 'correlation.' This data will be treated as corresponding to an additional measurements object (in addition to the qubits) because currently the node SingleQubitRBAnalysis creates a plot for each measurement object. However, the measurement object for the correlated data does not exist in any of the four variables discussed above.

## Guidelines for developers

A few guidelines for adding new functionality to analysis\_v3:

Writing nodes The node functions should be very narrow in scope, i.e. they should do one task only. For example: data filtering node, do preselection node, average node, rotate IQ node, rotate 1d array node, RabiAnalysis node, etc. Only make the node a class if it's absolutely necessary. So far, the only nodes that are classes are very specialized analyses like Rabi, single qubit RB, etc., which need to extract specific qubit parameters (old  $\pi$ -pulse amplitudes for example), fit, and plot based on the fit results. Maybe we can even come up with a way to not use classes at all! Moreover, all nodes must have data\_dict as the first input parameter. In addition, all nodes should also have the input parameters keys\_in and keys\_out. The former specifies the key(s) in the data\_dict corresponding to the data to be processed, while the latter specifies the key(s) that the node will create in the data\_dict and where the processed data will be placed. Please have a good reason for not using these input parameters in a node. All the nodes work with readout channels (specified in keys\_in), not with measurement objects (like qubits). Please make the node dependent on measurement object only if strictly necessary (for example if cal points or sweep points are used).

Adding nodes We should try to split up the node modules by concept as much as possible; for example: a module for plotting nodes, another for fitting nodes, etc. Feel free to make new modules, or split up existing ones if you think it makes sense. New node modules need to be imported in pipeline\_analysis.py and added to PipelineDataAnalysis.process\_data(), which is where the pipeline is parsed.

Helper functions Please try to write and use helper functions wherever possible! The advantage of these functions is that a particular functionality is implemented only once. Helper functions should be very narrow in scope. Two important helper functions that should be used in all nodes are get\_param and get\_data\_to\_process. The former provides a standard way to get a parameter. This function first tries to get it from they keyword arguments of the node, then from data\_dict, and lastly from experimental metadata, and can be told to raise an error if parameter is not found in any of these places. The latter helper function returns a dictionary of the form {key\_in: 1d\_array\_to\_process}, which is extracted from the data\_dict. The reason

this helper function exists is to allow for keys\_in to be None, in which case this function takes all the raw data channels, and to allow for keys\_in to be a path inside the data\_dict, with keys separated by '.' (ex: 'measured\_data.raw w0'). Another important helper function is get\_cp\_sp\_spmap\_measobjn, which extracts the cal points, the sweep points, the meas\_obj\_sweep\_points\_map, and the measurement object (we could consider including the meas\_obj\_value\_names\_map here as well, but so far I hardly ever used it). Finally, few useful helper functions for handling plot preparations are get\_cal\_sweep\_points (extends sweep points by number of cal points), get\_cal\_data (returns the data points that correspond to the cal points), and get\_msmt\_data (returns the data array without data points corresponding to cal points). All these helper functions are currently in the module helper\_functions.py. Feel free to add more helper functions, and/or to make new helper function modules to keep things conceptually separated.