# **Progress update**

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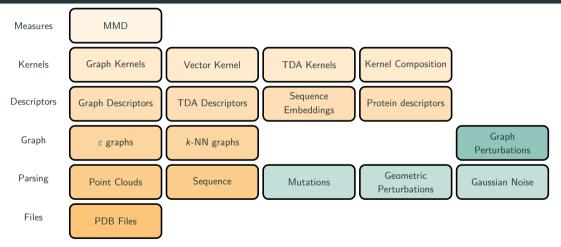
April 15, 2022



**D** BSSE



## **Overview**

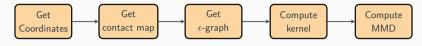


Green: perturbations

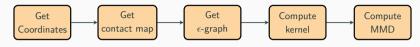
Orange: modules

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## Composable transformations & using sklearn API standards sensibly

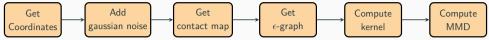


## Composable transformations & using sklearn API standards sensibly



What if we now want to add noise?

# Composable transformations & using sklearn API standards sensibly



```
base feature pipeline = pipeline.Pipeline(
        ("coordinates", Coordinates(granularity="CA", n_jobs=12),),
        ("contact map", ContactMap(metric="euclidean", n_jobs=12,),),
        ("epsilon graph", EpsilonGraph(epsilon=epsilon, n_jobs=12),),
proteins = base feature pipeline.fit transform(paths to pdb files)
mmd = MaximumMeanDiscrepancy(
    biased=True.
    squared=True.
    kernel=WeisfeilerLehmanKernel(
        n jobs=12, n iter=5, normalize=True, biased=True,
    ).
).compute(graphs, graphs perturbed)
```

```
base_feature_pipeline = pipeline.Pipeline(
        ("coordinates", Coordinates(granularity="CA", n jobs=12),),
            "add gaussian noise",
            GaussianNoise(
                random_seed=42, noise_mean=0, noise_variance=10, n_jobs=12,
            ).
        ("contact map", ContactMap(metric="euclidean", n jobs=12.).).
        ("epsilon graph", EpsilonGraph(epsilon=epsilon, n_jobs=12),),
proteins perturbed = base feature pipeline.fit transform(paths to pdb files)
graphs = load graphs(proteins, graph type="eps graph")
graphs perturbed = load graphs(proteins perturbed, graph type="eps graph")
mmd = MaximumMeanDiscrepancy(
    biased=True.
    squared=True,
    kernel=WeisfeilerLehmanKernel(
        n jobs=12, n iter=5, normalize=True, biased=True,
    ).
).compute(graphs, graphs_perturbed)
```

Reusable Components

But I want results!

## MMD experiments informs the best representation to use for proteins

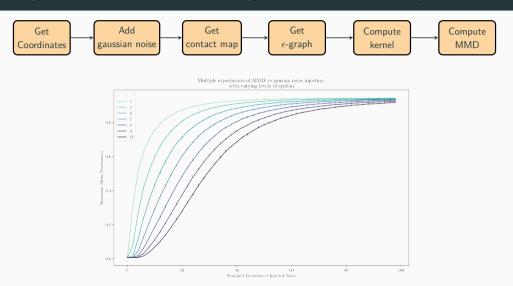


Figure 1: MMD as gaussian noise is added. Each bar is the 100% confidence interval over 10 runs.

## TDA captures morphological perturbations of proteins

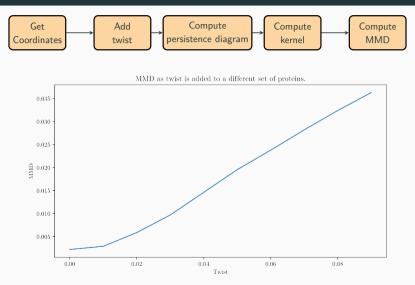
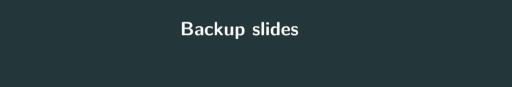


Figure 2: MMD value as twist is progressively added to a separate set of proteins.

1-sentence takeway

Parametrize your MMD sensibly for your protein generative model.



### **Detailed breakdown of modules**

#### Point clouds:

• Granularity can be set to  $\alpha$ -Carbon,  $\beta$ -Carbon, entire backbone or all-atom setting.

### Graph Descriptors:

- Degree Histogram
- Clustering Histogram
- Laplacian spectrum

### Topological Descriptors

- Persistence diagrams
- Persistence landscape
- Persistence image
- Betti Curves

Sequence Embeddings (ESM, different sizes)

### Protein Descriptors

- Ramachandran angles
- Interactomic clashes

Graph Kernels (Weisfeiler-Lehman Kernel)

Vector kernels (Linear, Gaussian)

TDA Kernel (Persistence Fisher Kernel)

Kernel composition  $(\times, +)$ 

MMD (Squared, biased)

#### **Perturbations**

Graph level (rewire, add/remove edge)

Point cloud perturbations (twist, taper, shear)

Protein perturbations (mutate)

All modules work on multiple proteins simultaneously

## The admin stuff

Message through slack for follow-up  $\ensuremath{\mathsf{Qs}}$ 

Extensive GitHub documentation & up-to-date codebase at

• https://github.com/pjhartout/msc\_thesis

Private repo a.t.m., message me to request access.