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# robust-laplacian 0.2.4

```
pip install robust-laplacian
```



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Released: Dec 14, 2021

Robust Laplace matrices for meshes and point clouds

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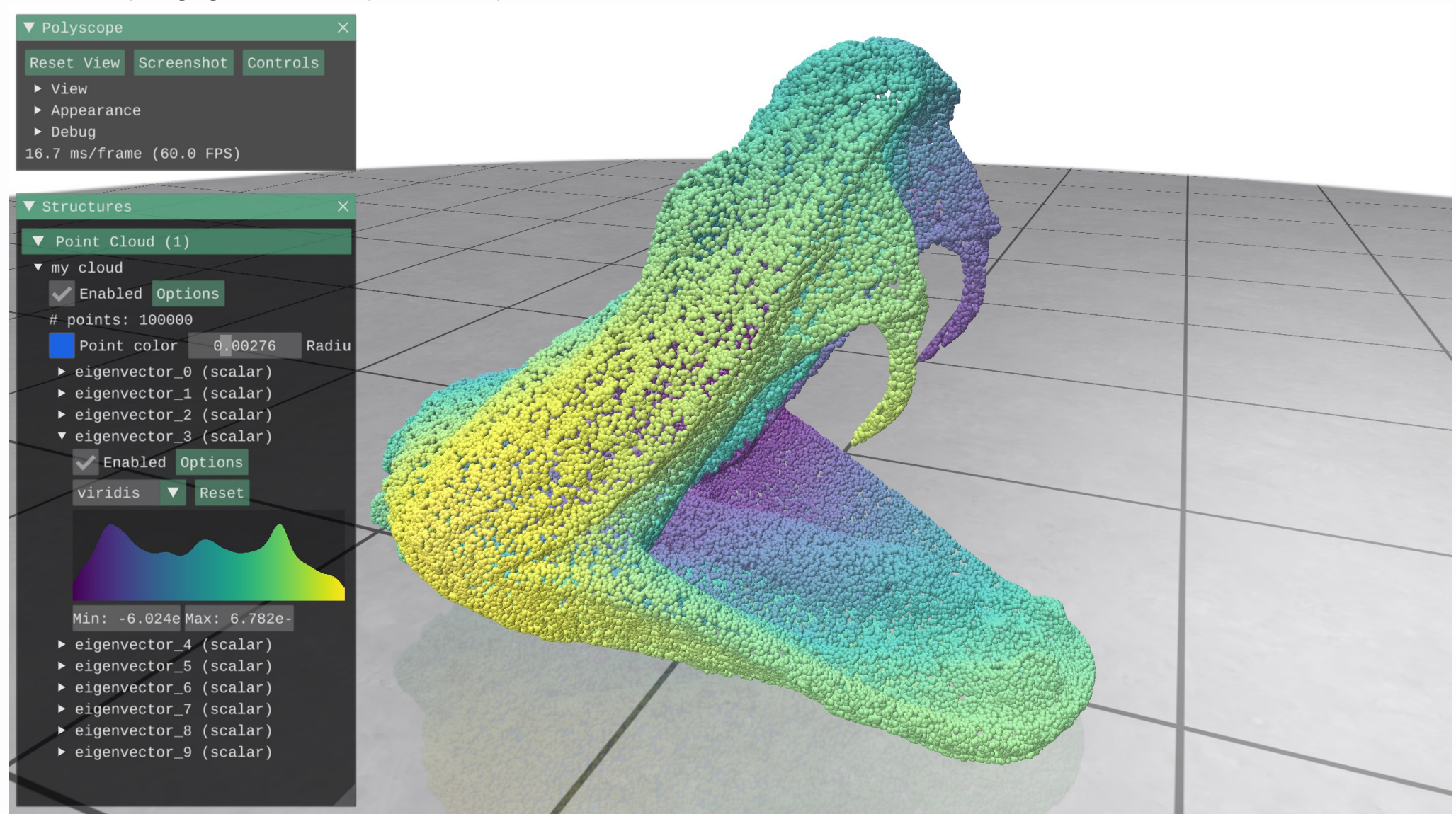
## Project description

 Test Linux passing  Test macOS passing  Test Windows passing  pypi v0.2.4

A Python package for high-quality Laplace matrices on meshes and point clouds. `pip install robust_laplacian`

The Laplacian is at the heart of many algorithms across geometry processing, simulation, and machine learning. This library builds a high-quality, robust Laplace matrix which often improves the performance of these algorithms, and wraps it all up in a simple, single-function API!

## Sample: computing eigenvectors of the point cloud Laplacian



Given as input a triangle mesh with arbitrary connectivity (could be nonmanifold, have boundary, etc), OR a point cloud, this library builds an  $N \times N$  sparse Laplace matrix, where  $N$  is the number of vertices/points. This Laplace matrix is similar to the *cotan-Laplacian* used widely in geometric computing, but internally the algorithm constructs an *intrinsic Delaunay triangulation* of the surface, which gives the Laplace matrix great numerical properties. The resulting

Laplacian is always a symmetric positive-definite matrix, with all positive edge weights. Additionally, this library performs *intrinsic mollification* to alleviate floating-point issues with degenerate triangles.

The resulting Laplace matrix  $L$  is a "weak" Laplace matrix, so we also generate a diagonal lumped mass matrix  $M$ , where each diagonal entry holds an area associated with the mesh element. The "strong" Laplacian can then be formed as  $M^{-1} L$ , or a Poisson problem could be solved as  $L x = M y$ .

A [C++ implementation and demo](#) is available.

This library implements the algorithm described in [A Laplacian for Nonmanifold Triangle Meshes](#) by [Nicholas Sharp](#) and [Keenan Crane](#) at SGP 2020 (where it won a best paper award!). See the paper for more details, and please use the citation given at the bottom if it contributes to academic work.

## Example

Build a point cloud Laplacian, compute its first 10 eigenvectors, and visualize with [Polyscope](#)

```
pip install numpy scipy plyfile polyscope robust_laplacian
```

```
import robust_laplacian
from plyfile import PlyData
import numpy as np
import polyscope as ps
import scipy.sparse.linalg as sla

# Read input
plydata = PlyData.read("/path/to/cloud.ply")
points = np.vstack((
    plydata['vertex']['x'],
    plydata['vertex']['y'],
    plydata['vertex']['z']
```

```

)).T

# Build point cloud Laplacian
L, M = robust_laplacian.point_cloud_laplacian(points)

# (or for a mesh)
# L, M = robust_laplacian.mesh_laplacian(verts, faces)

# Compute some eigenvectors
n_eig = 10
evals, evects = sla.eigsh(L, n_eig, M, sigma=1e-8)

# Visualize
ps.init()
ps_cloud = ps.register_point_cloud("my cloud", points)
for i in range(n_eig):
    ps_cloud.add_scalar_quantity("eigenvector_"+str(i), evects[:,i], enabled=True)
ps.show()

```

**NOTE:** No one can agree on the sign convention for the Laplacian. This library builds the *positive semi-definite* Laplace matrix, where the diagonal entries are positive and off-diagonal entries are negative. This is the *opposite* of the sign used by e.g. libIGL in `igl.cotmatrix`, so you may need to flip a sign when converting code.

## API

This package exposes just two functions:

- `mesh_laplacian(verts, faces, mollify_factor=1e-5)`
  - `verts` is an `V x 3` numpy array of vertex positions
  - `faces` is an `F x 3` numpy array of face indices, where each is a 0-based index referring to a vertex

- `mollify_factor` amount of intrinsic mollification to perform. `0` disables, larger values will increase numerical stability, while very large values will slightly implicitly smooth out the geometry. The range of reasonable settings is roughly `0` to `1e-3`. The default value should usually be sufficient.
- `return L, M` a pair of scipy sparse matrices for the Laplacian `L` and mass matrix `M`
- `point_cloud_laplacian(points, mollify_factor=1e-5, n_neighbors=30)`
  - `points` is an `V x 3` numpy array of point positions
  - `mollify_factor` amount of intrinsic mollification to perform. `0` disables, larger values will increase numerical stability, while very large values will slightly implicitly smooth out the geometry. The range of reasonable settings is roughly `0` to `1e-3`. The default value should usually be sufficient.
  - `n_neighbors` is the number of nearest neighbors to use when constructing local triangulations. This parameter has little effect on the resulting matrices, and the default value is almost always sufficient.
  - `return L, M` a pair of scipy sparse matrices for the Laplacian `L` and mass matrix `M`

## Installation

The package is available via `pip`

```
pip install robust_laplacian
```

The underlying algorithm is implemented in C++; the pypi entry includes precompiled binaries for many platforms.

Very old versions of `pip` might need to be upgraded like `pip install pip --upgrade` to use the precompiled binaries.

Alternately, if no precompiled binary matches your system `pip` will attempt to compile from source on your machine. This requires a working C++ toolchain, including cmake.

## Known limitations

- For point clouds, this repo uses a simple method to generate planar Delaunay triangulations, which may not be totally robust to collinear or degenerate point clouds.

## Dependencies

This python library is mainly a wrapper around the implementation in the [geometry-central](#) library; see there for further dependencies. Additionally, this library uses [pybind11](#) to generate bindings, and [jc\\_voronoi](#) for 2D Delaunay triangulation on point clouds. All are permissively licensed.

## Citation

```
@article{Sharp:2020:LNT,  
  author={Nicholas Sharp and Keenan Crane},  
  title={{A Laplacian for Nonmanifold Triangle Meshes}},  
  journal={Computer Graphics Forum (SGP)},  
  volume={39},  
  number={5},  
  year={2020}  
}
```

## For developers

This repo is configured with CI on github actions to build wheels across platform.

## Deploy a new version

- Commit the desired version to the `master` branch, be sure the version string in `setup.py` corresponds to the new version number. Include the string `[ci build]` in the commit message to ensure a build happens.

- Watch the github actions builds to ensure the test & build stages succeed and all wheels are compiled.
- While you're waiting, update the docs.
- Tag the commit with a tag like `v1.2.3`, matching the version in `setup.py`. This will kick off a new github actions build which deploys the wheels to PyPI after compilation.



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