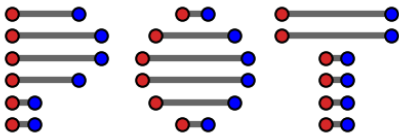


Optimal Transport in Python: A Practical Introduction with POT



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May 6th, 2026

Institut Henri Poincaré, Paris, France

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- (Fused) Gromov-Wasserstein

- Unbalanced and partial OT

- OT on Gaussians and Gaussian Mixtures

Conclusion and Q&A

History of POT

Origin story

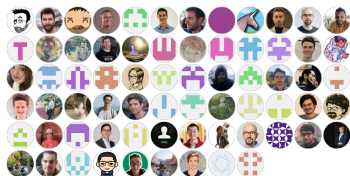
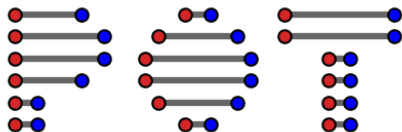
- Start collaboration with N. Courty and D. Tuia in 2014 on domain adaptation with OT [Courty et al., 2014].
- Original code in Matlab from M. Cuturi for Sinkhorn algorithm [Cuturi, 2013].
- Switch to Python OT solvers in 2015 for Sinkhorn (N. Courty) and network flow from A. Rolet (orig. Matlab wrapper) and N. Bonneel (C++ wrapper) in 2015.
- First Commit Oct 20th 2016, first release Oct 28th 2016 on PyPI.

From research software to maintained open source toolbox

- A. Gramfort joins in 2017, and helps to set up CI-CD, testing, documentation, and maintenance.
- POT on conda forge in 2017 (D. Sutherland).
- Published on JMLR open source software in 2021 [Flamary et al., 2021].
- POT on debian unstable in January 2021 (Gard Spreemann)
- C. Vincent Cuaz joins as co-maintainer in 2024.

Big thanks to all contributors and users!

POT General information



The toolbox

- Website/documentation: <https://pythonot.github.io/>
- Github: <https://github.com/PythonOT/POT>
- Activity: 84 contributors, 2.8k stars, 8.2 M PyPI downloads, 1600 citations.
- Features: OT solvers from 82 papers, 78 examples in gallery.
- CI-CD: 97% test coverage, 100% PEP8 compliant with pre-commit.
- Maintained since 2016: 2 releases/year, 1.6k commits.
- Packages in PyPI (POT), Conda forge, Debian, Ubuntu.

```
$ pip install pot
```

```
$ conda install -c conda-forge pot
```

```
$ sudo apt install python3-pot # ubuntu
```

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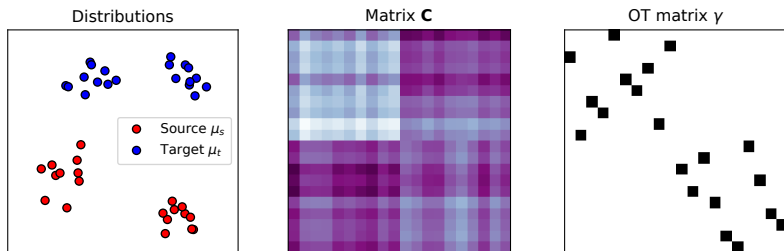
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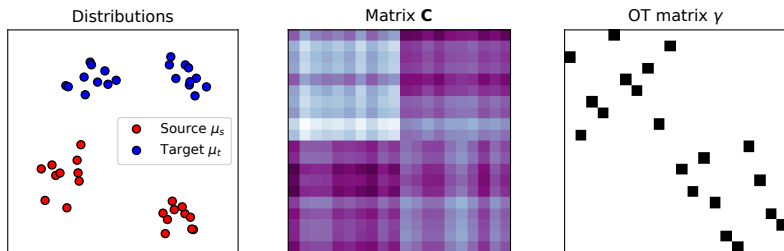
How to solve OT in Python?



Solving discrete OT with POT

```
1 import ot # import POT
2
3 # Xs and Xt are positions of source and target samples
4 C = ot.dist(Xs, Xt, metric = 'euclidean') # ground cost matrix
5 result = ot.solve(C, a=a, b=b) # returns an OTResult object
6
7 T = result.plan # get the OT plan
8 cost = result.value # get the OT cost
```

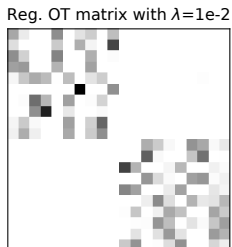
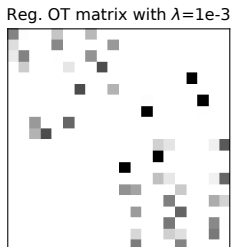
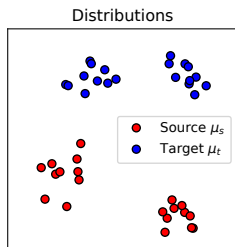
How to solve OT in Python?



Solving empirical discrete OT with POT

```
1 import ot # import POT
2
3 # Xs and Xt are positions of source and target samples
4 # default values uniform weights for a,b
5 result = ot.solve_sample(Xs, Xt, metric='euclidean')
6
7 T = result.plan # get the OT plan
8 cost = result.value # get the OT cost
```

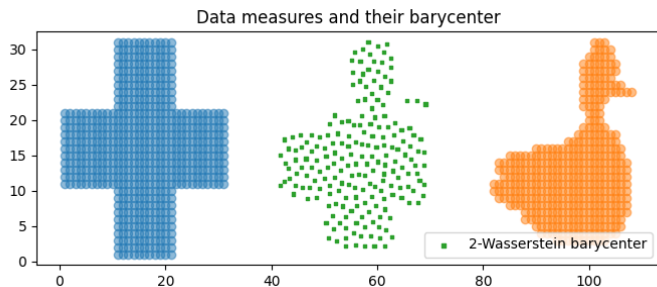
How to solve OT in Python?



Solving regularized discrete OT with POT (sinkhorn)

```
1 import ot # import POT
2
3 # Xs and Xt are positions of source and target samples
4 # reg is entropic regularization strength
5 result = ot.solve_sample(Xs, Xt, reg=0.1, metric='euclidean')
6
7 T = result.plan # get the OT plan
8 cost = result.value # get the OT cost
```

OT barycenter between empirical distributions



Wasserstein (free support) barycenter with POT

```
1 from ot.lp import free_support_barycenter
2
3 X_list = [X1, X2] # list of locations of the measures
4 a_list = [a1, a2] # list of weights of the measures
5 w = [0.5, 0.5] # barycenter weights
6 X_init = np.random.randn(k, d) # initial barycenter locations
7 Xbary = free_support_barycenter(X_list, a_list, X_init,
  ↪ weights=w)
```

Differentiable OT solvers : POT backends

POT Backends

- Automatic detection of type of inputs (Numpy, Pytorch, Tensorflow, Jax, Cupy).
- Coded in functions with the backend : `nx = get_backend(C,a,b, ...)` .
- Differentiation through the OT solvers (automatic or manual definition).
- Works with CPU and GPU tensors (similar to array-api)

Example in Pytorch

```
1 import ot
2 import torch
3
4 # differentiable loss (or OT plan)
5 Xs = torch.randn((100,2), requires_grad=True).cuda()
6 Xt = torch.randn((80,2)).cuda()
7 loss = ot.solve_sample(Xs, Xt, reg=0.1).value # runs on GPU
8 loss.backward() # gradients on Xs
9
10 # batched with C_batch a (batch, n, n) tensor of cost matrices
11 loss_batch = ot.solve_batch(C_batch, reg=0.1).value
12 loss_batch.mean().backward() # grads backprop. through C_batch
```

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- (Fused) Gromov-Wasserstein

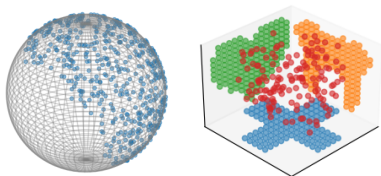
- Unbalanced and partial OT

- OT on Gaussians and Gaussian Mixtures

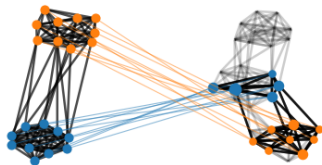
Conclusion and Q&A

Advanced features : other solvers in POT

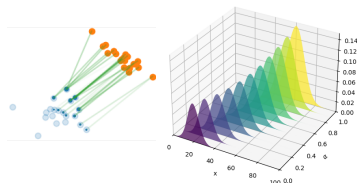
Sliced OT (line, sphere, subspace)



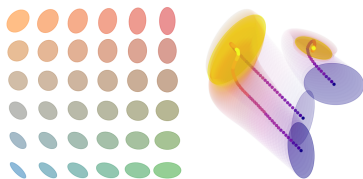
(Fused) Gromov-Wasserstein OT



Unbalanced and partial OT



OT on Gaussian and Gaussian mixtures



Example Gallery: https://pythonot.github.io/auto_examples/index.html

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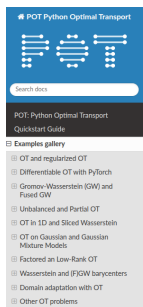
POT contributors



Fundings



Conclusions and Q&A

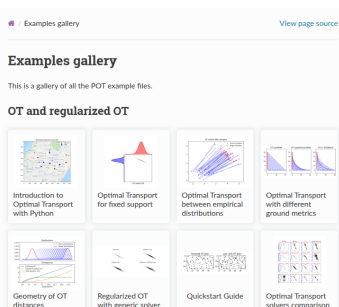


POT Python Optimal Transport
Quickstart Guide

Search docs

Examples gallery

- OT and regularized OT
- Differentiable OT with PyTorch
- Gromov-Wasserstein (GW) and Fused GW
- Unbalanced and Partial OT
- OT in 1D and Sliced Wasserstein
- OT on Gaussian and Gaussian Mixture Models
- Factored on Low-Rank OT
- Wasserstein and (F)GW barycenters
- Domain adaptation with OT
- Other OT problems



Examples gallery

This is a gallery of all the POT example files.

OT and regularized OT

- Introduction to Optimal Transport with Python
- Optimal Transport for fixed support
- Optimal Transport between empirical distributions
- Optimal Transport with different ground metrics
- Geometry of OT distances
- Regularized OT with generic solver
- Quickstart Guide
- Optimal Transport solvers comparison

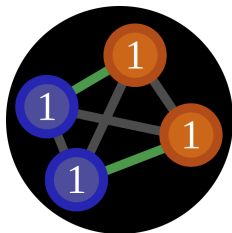
Link to slides



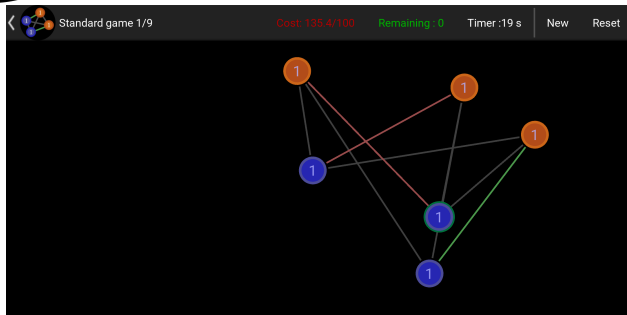
Optimal Transport in Python

- POT is a well established library for optimal transport in Python.
- Both basic and more advanced OT solvers from the literature implemented.
- Backends for Numpy/Scipy, Pytorch, Cupy, Tensorflow and Jax.
- Many other examples in the gallery: <https://pythonot.github.io/>
- Other open source libraries: GeomLoss, OTT-JAX, SDOT.

OTGame (OT Puzzle game on android)

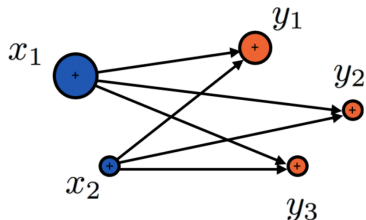
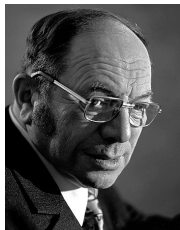


OTGame



<https://play.google.com/store/apps/details?id=com.flamary.otgame>

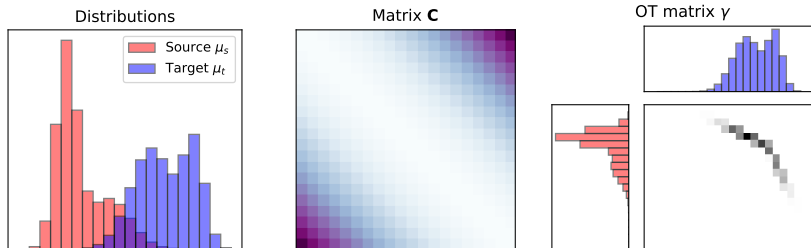
Optimal transport



Principle: Move mass in the most efficient way

- Problem introduced by Gaspard Monge in his memoire [Monge, 1781].
- Monge formulation seeks for a mapping between two mass distribution.
- Reformulated by Leonid Kantorovich to allow splitting [Kantorovich, 1942].
- Applications originally for resource allocation problems

Discrete Optimal Transport



Kantorovitch formulation : OT Linear Program

When $\mu_s = \sum_{i=1}^{n_s} a_i \delta_{\mathbf{x}_i^s}$ and $\mu_t = \sum_{i=1}^{n_t} b_i \delta_{\mathbf{x}_i^t}$

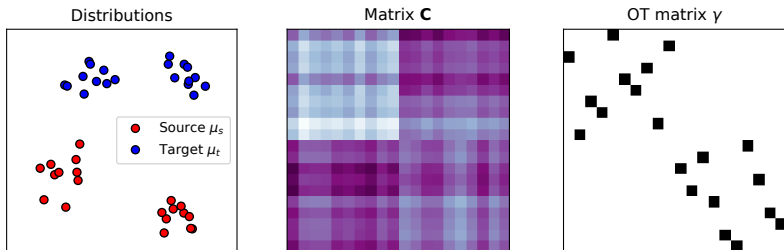
$$W_p^p(\mu_s, \mu_t) = \min_{T \geq 0} \sum_{i,j} T_{i,j} C_{i,j}$$

$$\text{s.t.} \quad \sum_j T_{i,j} = a_i, \forall i \quad \text{and} \quad \sum_i T_{i,j} = b_j, \forall j$$

where \mathbf{C} is a cost matrix with $C_{i,j} = c(\mathbf{x}_i^s, \mathbf{x}_j^t) = \|\mathbf{x}_i^s - \mathbf{x}_j^t\|^p$

- Solving the OT problem with network simplex is $O(n^3 \log(n))$ for $n = n_s = n_t$.
- $W_p(\mu_s, \mu_t)$ is called the Wasserstein distance (EMD for $p = 1$).

Discrete Optimal Transport



Kantorovitch formulation : OT Linear Program

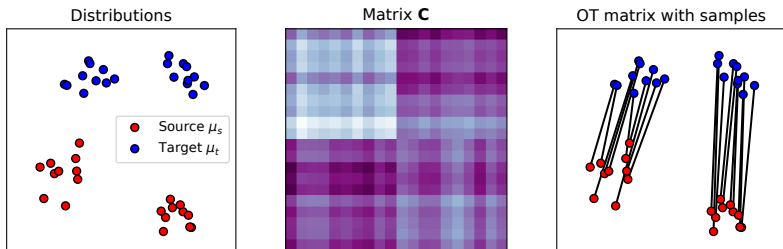
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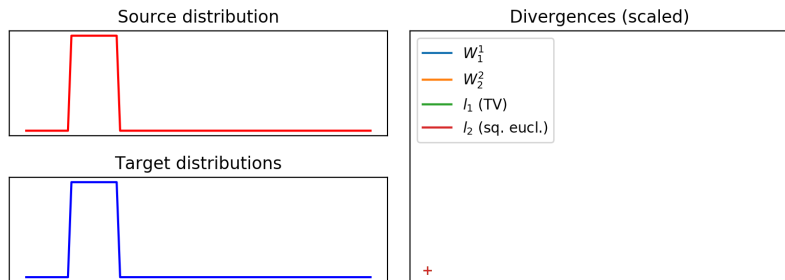
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Wasserstein distance



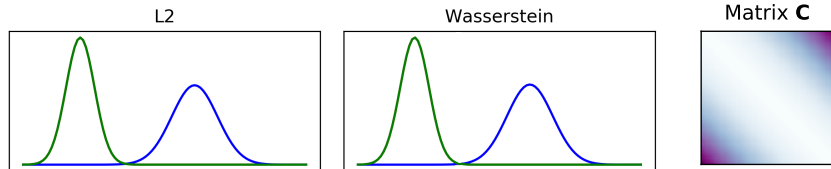
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In this case we have $c(\mathbf{x}, \mathbf{y}) = \|\mathbf{x} - \mathbf{y}\|^p$

- A.K.A. Earth Mover's Distance (W_1^1) [Rubner et al., 2000].
- Useful between discrete distribution even without overlapping support.
- Smooth approximation can be computed with Sinkhorn [Cuturi, 2013].
- **Wasserstein barycenter**: $\bar{\mu} = \arg \min_{\mu} \sum_i w_i W_2^2(\mu, \mu_i)$

Wasserstein distance



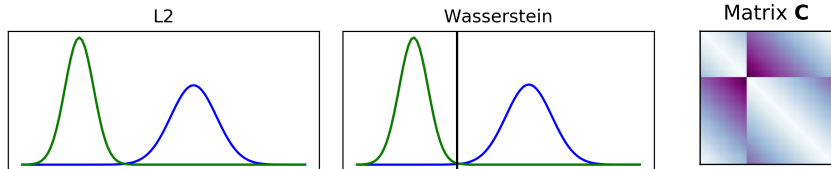
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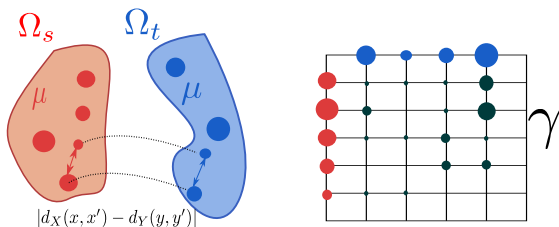
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Gromov-Wasserstein and extensions



Inspired from Gabriel Peyré

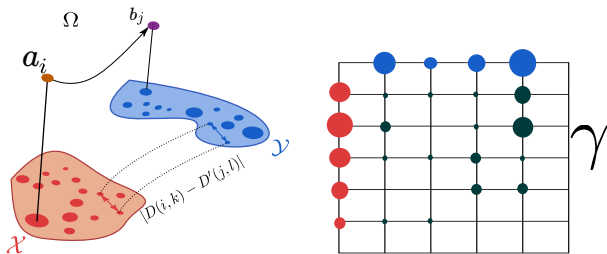
GW for discrete distributions [Memoli, 2011]

$$GW_p^p(\mu_s, \mu_t) = \min_{T \in \Pi(\mu_s, \mu_t)} \sum_{i,j,k,l} |D_{i,k} - D'_{j,l}|^p T_{i,j} T_{k,l}$$

with $\mu_s = \sum_i a_i \delta_{\mathbf{x}_i^s}$ and $\mu_t = \sum_j b_j \delta_{\mathbf{x}_j^t}$ and $D_{i,k} = \|\mathbf{x}_i^s - \mathbf{x}_k^s\|$, $D'_{j,l} = \|\mathbf{x}_j^t - \mathbf{x}_l^t\|$

- Distance between metric measured spaces : across different spaces.
- Search for an OT plan that preserve the pairwise relationships between samples.
- Entropy regularized GW proposed in [Peyré et al., 2016].
- Fused GW interpolates between Wass. and GW [Vayer et al., 2018].

Gromov-Wasserstein and extensions



FGW for discrete distributions [Vayer et al., 2018]

$$FGW_p^p(\mu_s, \mu_t) = \min_{T \in \Pi(\mu_s, \mu_t)} \sum_{i,j,k,l} ((1-\alpha)C_{i,j}^q + \alpha|D_{i,k} - D'_{j,l}|^q)^p T_{i,j} T_{k,l}$$

with $\mu_s = \sum_i a_i \delta_{\mathbf{x}_i^s}$ and $\mu_t = \sum_j b_j \delta_{\mathbf{x}_j^t}$ and $D_{i,k} = \|\mathbf{x}_i^s - \mathbf{x}_k^s\|$, $D'_{j,l} = \|\mathbf{x}_j^t - \mathbf{x}_l^t\|$

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OT for Machine Learning and Data Science



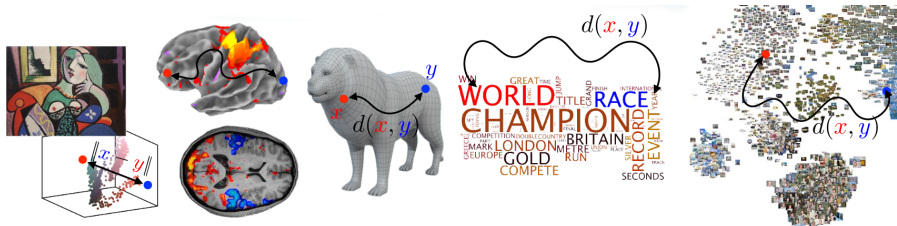
Distributions are everywhere in machine learning

- Images, vision, graphics, Time series, text, genes, proteins.
- Many datum and datasets can be seen as distributions.
- Optimal transport provides tools for comparing them with a meaningful geometry.

How to use OT for ML?

- As a loss to compare distributions (Wasserstein distance).
- To learn a mapping between distributions (OT mapping).
- To learn on non-standard data (structured data, graphs).

OT for Machine Learning and Data Science



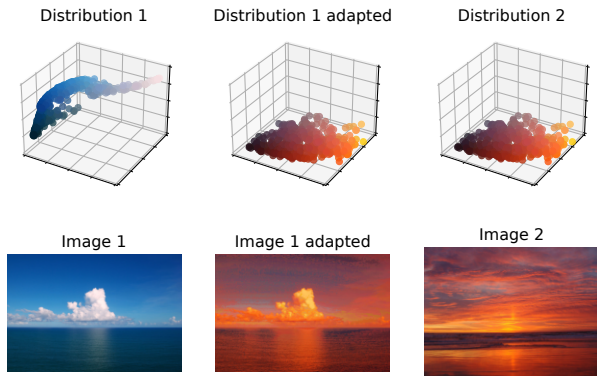
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OT for images processing and graphics



Applications of OT for images processing and graphics

- Transporting pixels for color transfer [Ferradans et al., 2014].
- Transporting image patches for style transfer [Mroueh, 2019].
- Shape interpolation with OT barycenters [Solomon et al., 2015].

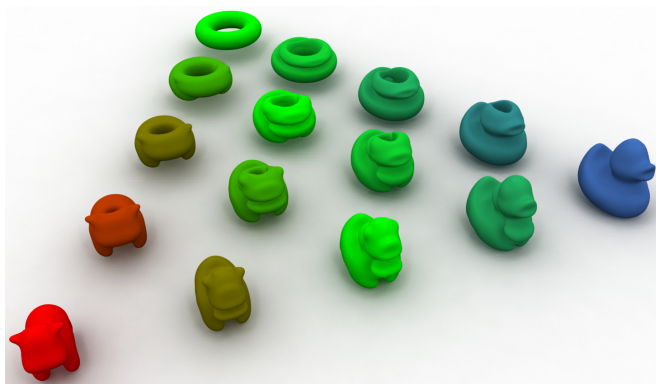
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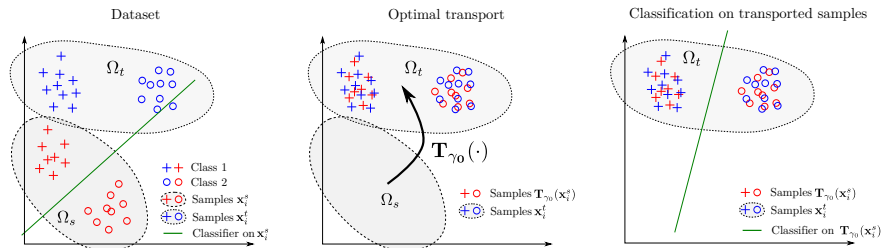
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Optimal Transport for Domain Adaptation



Transport the data [Courty et al., 2016]

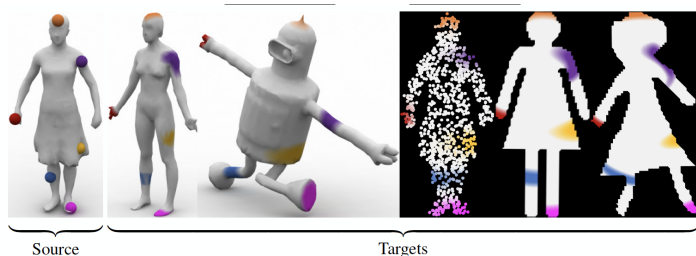
1. Estimate optimal transport between distributions.
2. Transport the training samples on target domain.
3. Learn a classifier on the transported training samples.

Can also be used to compensate for biased datasets [Gordaliza et al., 2019]

Transport the labels

- Label Propagation using OT matrix [Solomon et al., 2014, Redko et al., 2019].
- Optimize the target classifier [Courty et al., 2017, Damodaran et al., 2018].
- Change in proportion of classes [Redko et al., 2019, Rakotomamonjy et al., 2020].

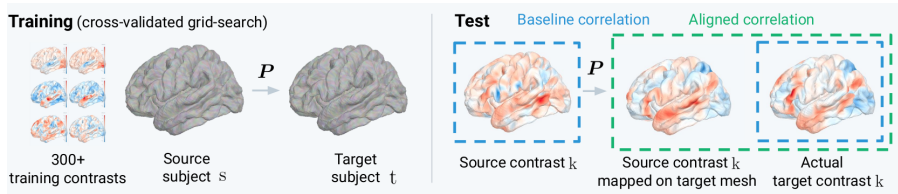
OT between graphs



Gromov-Wasserstein OT distance [Memoli, 2011]

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 - Brain MRI alignment [Thual et al., 2022]
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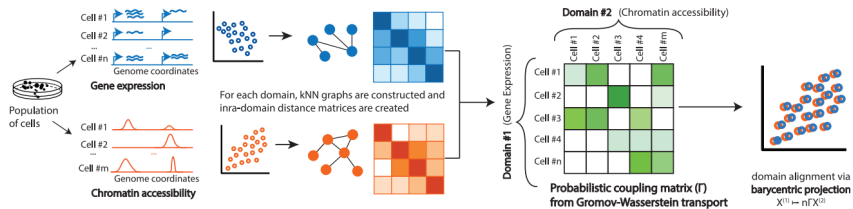
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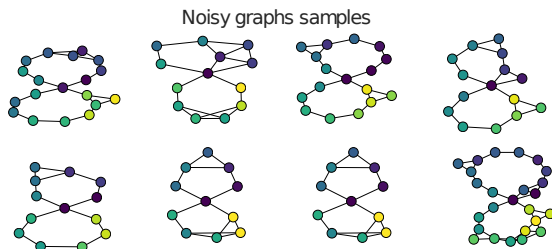
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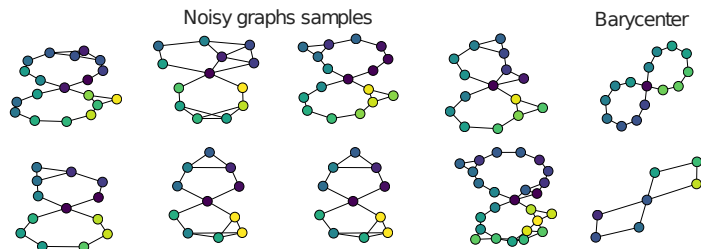
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References I

- [Courty et al., 2014] Courty, N., Flamary, R., and Tuia, D. (2014).
Domain adaptation with regularized optimal transport.
In European Conference on Machine Learning and Principles and Practice of Knowledge Discovery in Databases (ECML PKDD).
- [Courty et al., 2016] Courty, N., Flamary, R., Tuia, D., and Rakotomamonjy, A. (2016).
Optimal transport for domain adaptation.
Pattern Analysis and Machine Intelligence, IEEE Transactions on.
- [Courty et al., 2017] Courty, N., Flamary, R., Tuia, D., and Rakotomamonjy, A. (2017).
Optimal transport for domain adaptation.
IEEETPAMI, 39(9):1853–1865.
- [Cuturi, 2013] Cuturi, M. (2013).
Sinkhorn distances: Lightspeed computation of optimal transport.
In NIPS, pages 2292–2300.
- [Damodaran et al., 2018] Damodaran, B. B., Kellenberger, B., Flamary, R., Tuia, D., and Courty, N. (2018).
Deepjdot: Deep joint distribution optimal transport for unsupervised domain adaptation.

References II

- [Demetci et al., 2022] Demetci, P., Santorella, R., Chakravarthy, M., Sandstede, B., and Singh, R. (2022).
Scotv2: Single-cell multiomic alignment with disproportionate cell-type representation.
Journal of Computational Biology, 29(11):1213–1228.
- [Ferradans et al., 2014] Ferradans, S., Papadakis, N., Peyré, G., and Aujol, J.-F. (2014).
Regularized discrete optimal transport.
SIAM Journal on Imaging Sciences, 7(3):1853–1882.
- [Flamary et al., 2021] Flamary, R., Courty, N., Gramfort, A., Alaya, M. Z., Boisbunon, A., Chambon, S., Chapel, L., Corenflos, A., Fatras, K., Fournier, N., Gautheron, L., Gayraud, N. T., Janati, H., Rakotomamonjy, A., Redko, I., Rolet, A., Schutz, A., Seguy, V., Sutherland, D. J., Tavenard, R., Tong, A., and Vayer, T. (2021).
Pot: Python optimal transport.
Journal of Machine Learning Research, 22(78):1–8.
- [Gordaliza et al., 2019] Gordaliza, P., Del Barrio, E., Fabrice, G., and Loubes, J.-M. (2019).
Obtaining fairness using optimal transport theory.
In *International Conference on Machine Learning*, pages 2357–2365. PMLR.

References III

[Kantorovich, 1942] Kantorovich, L. (1942).

On the translocation of masses.

C.R. (Doklady) Acad. Sci. URSS (N.S.), 37:199–201.

[Memoli, 2011] Memoli, F. (2011).

Gromov wasserstein distances and the metric approach to object matching.

Foundations of Computational Mathematics, pages 1–71.

[Monge, 1781] Monge, G. (1781).

Mémoire sur la théorie des déblais et des remblais.

De l’Imprimerie Royale.

[Mroueh, 2019] Mroueh, Y. (2019).

Wasserstein style transfer.

arXiv preprint arXiv:1905.12828.

[Peyré et al., 2016] Peyré, G., Cuturi, M., and Solomon, J. (2016).

Gromov-wasserstein averaging of kernel and distance matrices.

In *ICML*, pages 2664–2672.

References IV

- [Rakotomamonjy et al., 2020] Rakotomamonjy, A., Flamary, R., Gasso, G., Alaya, M., Berar, M., and Courty, N. (2020).
Match and reweight strategy for generalized target shift.
- [Redko et al., 2019] Redko, I., Courty, N., Flamary, R., and Tuia, D. (2019).
Optimal transport for multi-source domain adaptation under target shift.
In *International Conference on Artificial Intelligence and Statistics (AISTAT)*.
- [Rubner et al., 2000] Rubner, Y., Tomasi, C., and Guibas, L. J. (2000).
The earth mover's distance as a metric for image retrieval.
International journal of computer vision, 40(2):99–121.
- [Solomon et al., 2015] Solomon, J., De Goes, F., Peyré, G., Cuturi, M., Butscher, A., Nguyen, A., Du, T., and Guibas, L. (2015).
Convolutional wasserstein distances: Efficient optimal transportation on geometric domains.
ACM Transactions on Graphics (TOG), 34(4):66.
- [Solomon et al., 2016] Solomon, J., Peyré, G., Kim, V. G., and Sra, S. (2016).
Entropic metric alignment for correspondence problems.
ACM Transactions on Graphics (TOG), 35(4):72.

References V

- [Solomon et al., 2014] Solomon, J., Rustamov, R., Guibas, L., and Butscher, A. (2014). Wasserstein propagation for semi-supervised learning. In *International Conference on Machine Learning*, pages 306–314. PMLR.
- [Thual et al., 2022] Thual, A., Tran, H., Zemskova, T., Courty, N., Flamary, R., Dehaene, S., and Thirion, B. (2022). Aligning individual brains with fused unbalanced gromov-wasserstein. In *Neural Information Processing Systems (NeurIPS)*.
- [Tran et al., 2023] Tran, Q. H., Janati, H., Courty, N., Flamary, R., Redko, I., Demetci, P., and Singh, R. (2023). Unbalanced co-optimal transport. In *Thirty-Seventh AAAI Conference on Artificial Intelligence (AAAI)*.
- [Vayer et al., 2018] Vayer, T., Chapel, L., Flamary, R., Tavenard, R., and Courty, N. (2018). Fused gromov-wasserstein distance for structured objects: theoretical foundations and mathematical properties.