

Migration Prediction

Team: Yellow Fish

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- The circular plot shows the estimates of directional flows between the 50 countries that send and/or receive at least 0.5% of the world's migrants in 2005–10. Tick marks indicate gross migration (in + out) in 100,000's.

Future work

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Move forward to other fields, for example:

- The migration between HTC and Apple.
- Employee migration between companies.
- etc.

Data collection

Data collection – Feature

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Features: total 741 = 738 individual + 3 inter-country

Individual country:

- Economy Development ([Worldbank](#))
- Health, Society index ([Worldbank](#))
- Climate ([Worldbank](#))
- Religion ([United nation](#))

Inter-country:

- Language similarity ([CEPII research](#))
- Geometric distance ([CEPII research](#))
- Trading ([Comtrade](#))

Data collection – Validation

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Migration data:

- From: [United nation Department of Economic and Social Affairs](#)
- Year: 2005, 2010, 2015

Feature extraction

Feature extraction – PCA

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- Linear extraction
- Fill in missing values with mean
- All data is numerical (no categorical data)
- Tool : scikit-learn

Feature extraction – Autoencoder

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- One hidden layer
 - input: x , output: y
 - $x' = \text{sigmoid}(w x)$
 - $y = \text{sigmoid}(w_2 x')$
- Loss function: $(x - y)^2$
- Extracted features: $x' = \text{sigmoid}(wx)$
- tool : Tensorflow

Basic method (for comparison)

Baseline

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Notation: let $x_{i,j}$ be the migration number predicted move from C_i to C_j , where C_i and C_j are countries.

Concept: Solve the linear equation.

$$\forall i, \sum_j x_{ij} = Mout_i$$

$$\forall j, \sum_i x_{ij} = Min_j$$

Solution: Proportional allocation

$$\forall C_i, x_{i,i} = 0$$

$$\forall i, j \text{ where } i \neq j, \text{ we have } x_{i,j} = \frac{Mout_i}{\sum_{k \neq i} Mout_k} Min_j$$

Supervised (not baseline)

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Concept: Use year A with features & real migration number to predict year B with only features.

Solution: SVM (Support vector machine) with feature extraction method mentioned before.

Unsupervised method

Linear score function & Quadratic Programming (1)

- After dimension reduction, we get k-dimension features f_{ij} for each pair of countries.
- **linear score function** : $S_{ij} = \sum_k w_k f_{ijk} = w^T f_{ij}$
- **objective function** : $\min f = \sum_i ((\sum_j S_{ij}) - O_i)^2 + \sum_j ((\sum_i S_{ij}) - I_j)^2$,
subject to $(f_{ij})^T w \geq 0, \forall i, j$ and $(f_{ii})^T w = 0, \forall i$

$$\begin{bmatrix} S_{11} & S_{12} & S_{13} & \dots & S_{1n} \\ S_{21} & S_{22} & S_{23} & \dots & S_{2n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ S_{n1} & S_{n2} & S_{n3} & \dots & S_{nn} \end{bmatrix} \begin{bmatrix} O_1 \\ O_2 \\ \vdots \\ O_n \end{bmatrix}$$
$$\begin{bmatrix} I_1 & I_2 & I_3 & \dots & I_n \end{bmatrix}$$

Linear score function & Quadratic Programming (2)

- Some mathematical derivation : let's focus on the left part

$$\sum_i ((\sum_j S_{ij}) - O_i)^2$$

$$= \sum_i ((\sum_j S_{ij})^2 - 2O_i(\sum_j S_{ij}) + O_i^2)$$

$$= \sum_i ((\sum_j w^T f_{ij})^2 - 2O_i(\sum_j w^T f_{ij}) + O_i^2)$$

$$= \sum_i (w^T M_i w + (-2O_i \sum_j f_{ij})^T w + O_i^2)$$

, where M_i is a $k * k$ diagonal matrix with $M_{i,kk} = (\sum_j f_{ijk})^2$

$$= w^T (\sum_i M_i) w + (-2 \sum_j O_i \sum_j f_{ij})^T w + \sum_i O_i^2$$

Linear score function & Quadratic Programming (3)

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- After omitting the constants,

$$f = w^T (\sum_i M_i + \sum_j M_j) w + (-2(\sum_j O_i \sum_j f_{ij} + \sum_i I_j \sum_i f_{ij}))^T w$$

and the problem become a **QP**(quadratic programming) problem with linear constraints!

- Since $(\sum_i M_i + \sum_j M_j)$ is **positive definite**, the problem can be solved in polynomial time.
- tool - [cvxopt](#)

Experiment result

Evaluation method

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- L1 loss divided by #entries

$$loss = \frac{\sum_{x \in X} |f(x) - y|}{|X|}$$

Result

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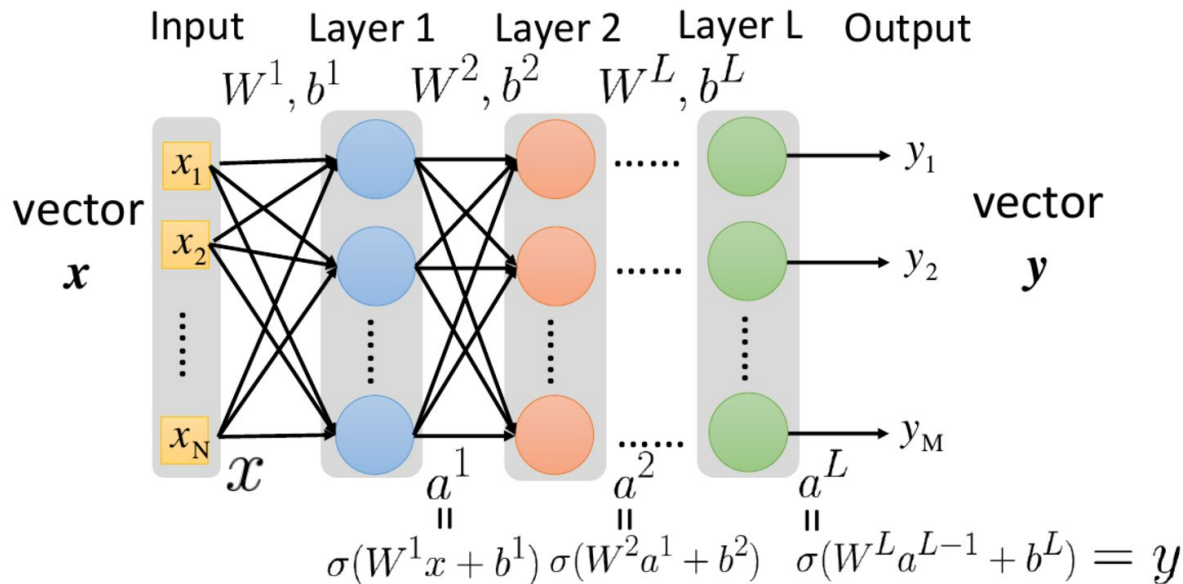
method	loss	Feature extraction	parameters
Baseline	20704.3	x	
Supervised	6967.5	PCA	dim=100, kernel='rbf'
Supervised	6965.7	AE	dim=100, kernel='rbf'
QP	16028.5	PCA	dim=50
QP	18045.3	PCA	dim=100
QP	18045.3	PCA	dim=200

What's next?

Try non-linear score function(1/2)

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Use neural network to turn linear score function into nonlinear.



Try non-linear score function (2/2)

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- Linear score function:

$$S = \Sigma w_1 x$$

- Nonlinear score function:

$$z_i^{(l)} = \sigma(w_{l-1} a_i^{(l-1)})$$

- Activation function: could be *tanh*, *sigmoid*, *Relu*
- Objective function: the same as with linear score function

$$\Sigma_i ((\Sigma_j S_{ij}) - O_i)^2 + \Sigma_j ((\Sigma_i S_{ij}) - I_j)^2$$

- Train: (Stochastic) Gradient Descent

Reference

Reference

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1. Supervised method: [Scikit-learn SVM](#)
2. Data: [Worldbank](#)
3. Data: [United nation](#)
4. Data: [CEPII research](#)
5. Data: [Comtrade](#)
6. Data: [United nation Department of Economic and Social Affairs](#)
7. PCA: [Scikit-learn PCA](#)
8. AE: [tensorflow](#)
9. QP: [cvxopt](#)

Thank you!