Resource-efficient Machine Learning

March 16th, 2016

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What can we do with machine learning these days?

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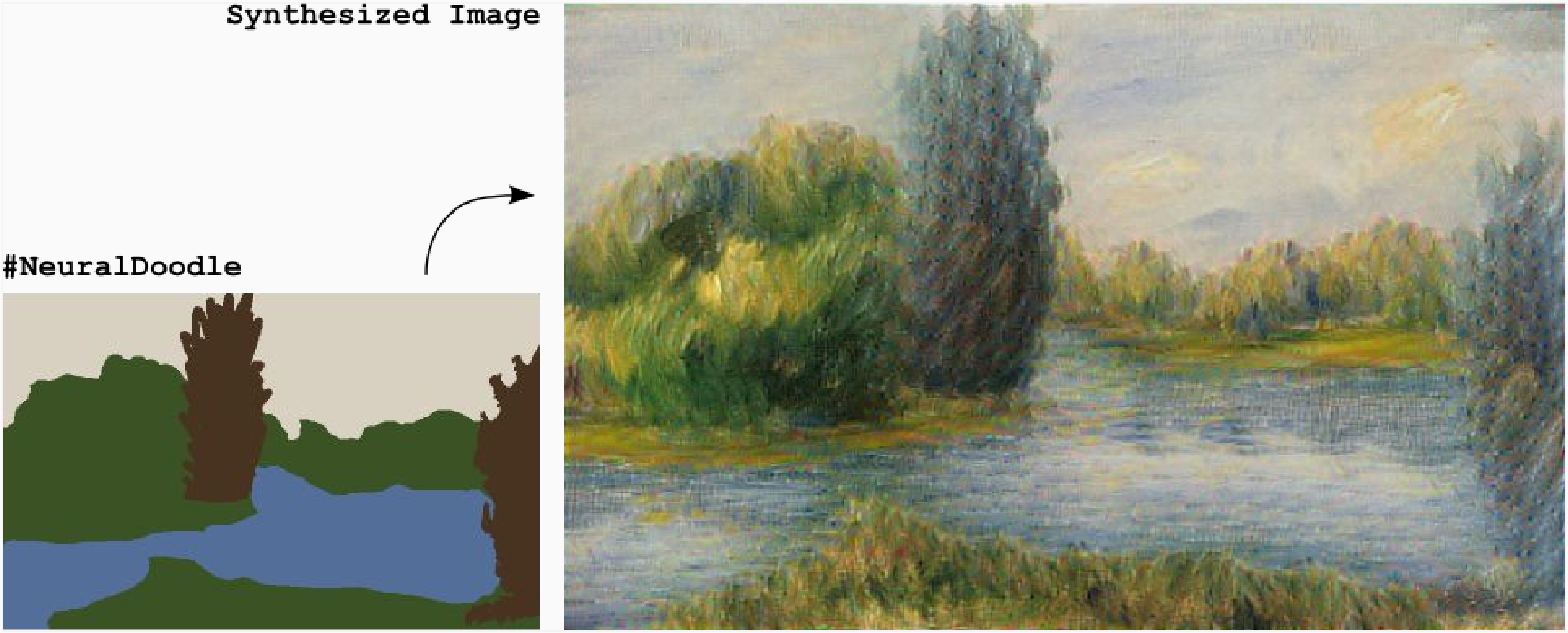
- We can paint pictures!



Source: Champandard (2016)

NeuralDoodle: Turning Two-Bit Doodles into Fine Artwork

What can we do with machine learning these days?

- We can paint pictures!
- We can beat top-ranked players at Go!

sam byford
@345triangle

Follow

lee se-dol leaves the match room bathed in camera flashes after historic defeat to deepmind theverge.com/2016/3/9/11184 …

AlphaGo beats Lee Se-dol in first of five matches

What can we do with machine learning these days?

- We can paint pictures!
- We can beat professionals at Go!

What can we do with machine learning these days?

- We can paint pictures!
  - Optimization problems
  - i.e. we can approximate unknown functions

$$\mathcal{L}_{total}(\vec{p}, \vec{a}, \vec{x}) = \alpha \mathcal{L}_{content}(\vec{p}, \vec{x}) + \beta \mathcal{L}_{style}(\vec{a}, \vec{x})$$

SWEDISH ICT SICS

What can we do with machine learning these days?

- We can paint pictures!
  - Optimization problems
  - i.e. we can approximate unknown functions
- We can beat professionals at Go!
  - Probabilistic problems
  - i.e. we can also approximate unknown distributions*

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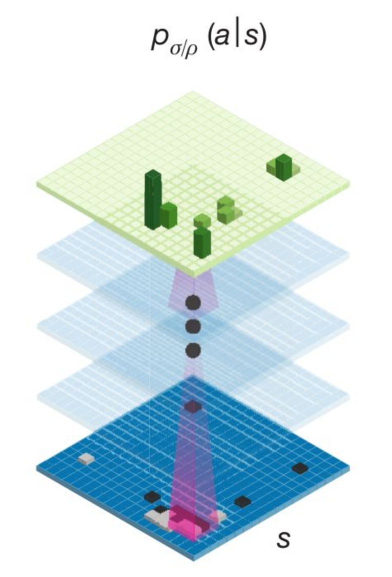

*definition abuse warning, see Silver et al. (2016) for details

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How can we do “resource-efficient” Machine Learning?

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  - Systems

How can we do “resource-efficient” Machine Learning?

- Two ways to look at the problem:
  - Algorithms
    - Create smarter algorithms and use math tricks to reduce computations
  - Systems
    - Ensure that computations are efficient and minimize communication

Resource efficient algorithms

Resource-efficient algorithms

- “Sum all numbers from 1 to 100”
  - 1 + 2 + 3 + … = ?

Resource-efficient algorithms

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    - 50 × 101 = 5050

Resource-efficient algorithms

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  - 1 + 2 + 3 + … = ?
  - 1+100=101, 2+99=101, 3+98=101, ..., 50+51=101.
    - 50 × 101 = 5050
  - sum(1...n) = n(n+1)/2

Resource-efficient deep learning

- *“Structured Transforms for Small-footprint Deep Learning”*, Sindhwani et al., NIPS 2015

Resource-efficient deep learning

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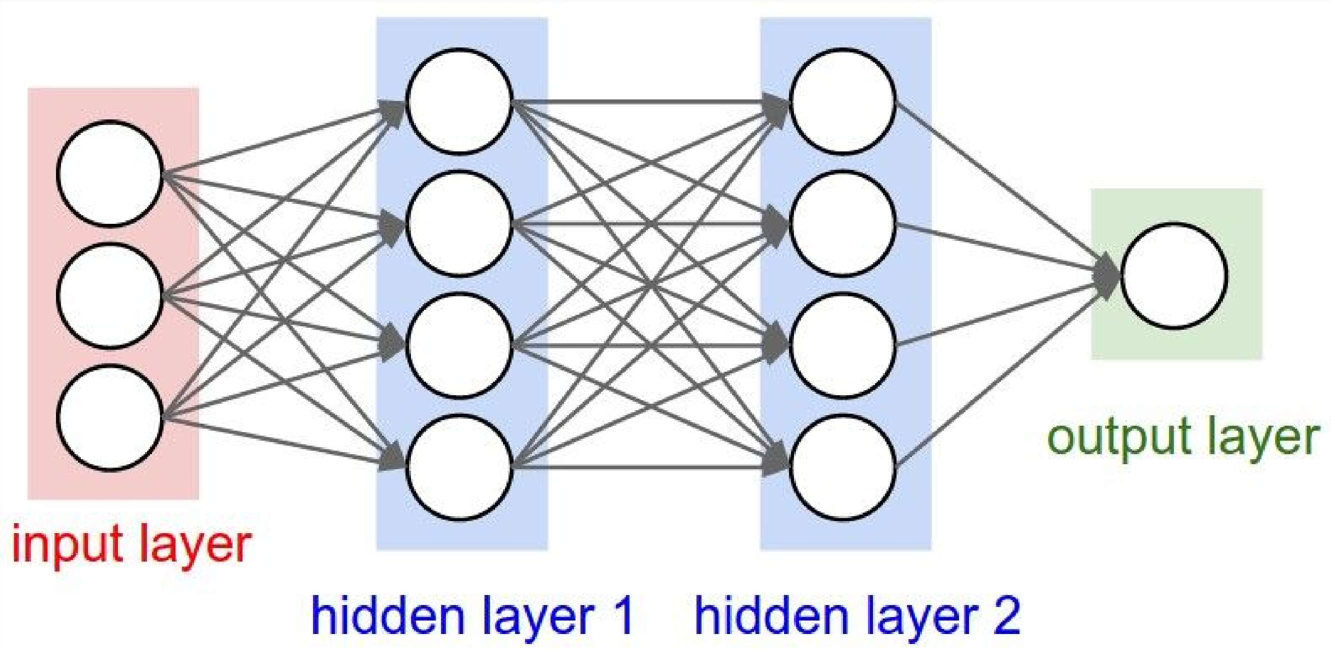
- Deep learning = Neural Networks (NN) = Matrix math (Linear algebra)



Source: Karpathy

Resource-efficient deep learning

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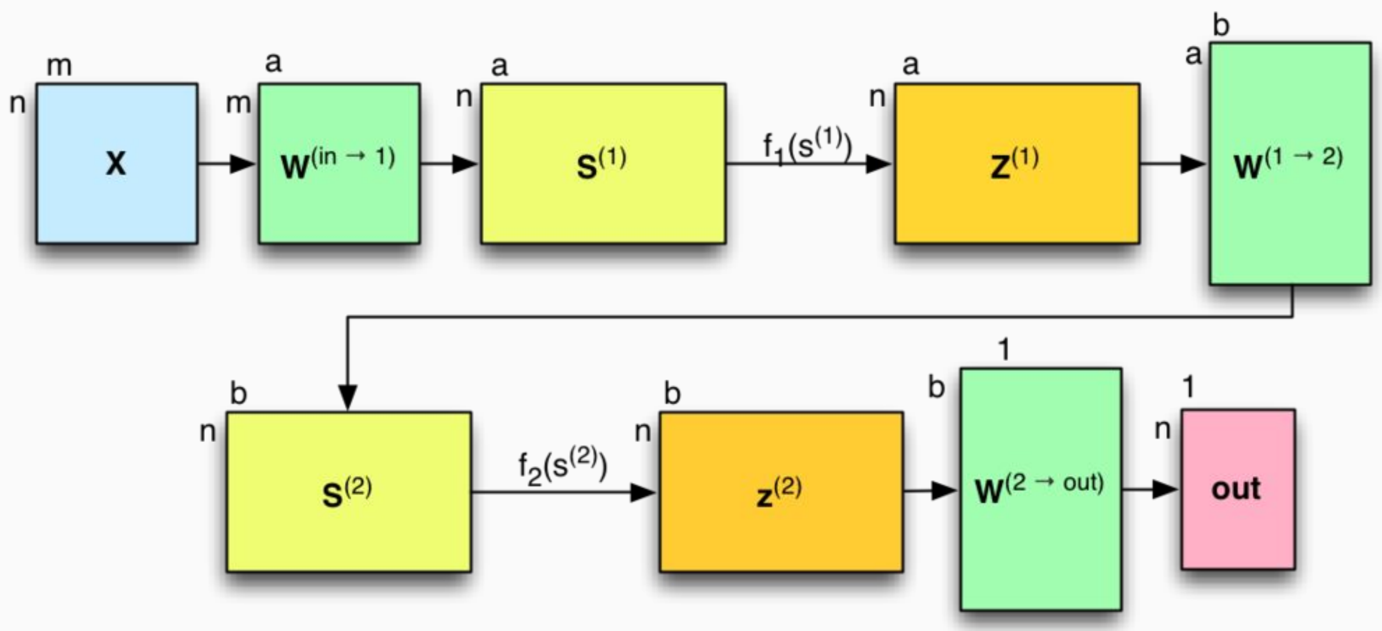


Source: Dolhansky

Resource-efficient deep learning

- *Structured matrices*: Matrices whose elements exhibit a common structure, e.g in a Toeplitz matrix each diagonal is constant:

$$\begin{bmatrix} t_0 & t_{-1} & \cdots & t_{-(n-1)} \\ t_1 & t_0 & \cdots & \vdots \\ \vdots & \vdots & \vdots & t_{-1} \\ t_{n-1} & \cdots & t_1 & t_0 \end{bmatrix}$$

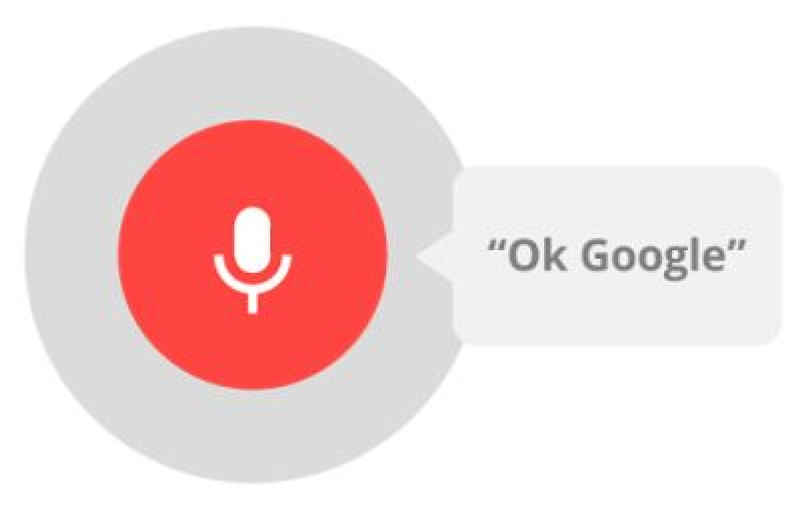
Resource-efficient deep learning

- Idea: Represent NN matrices as combinations of Toeplitz matrices, allowing us to do “superfast” linear algebra

$$\begin{bmatrix} t_0 & t_{-1} & \cdots & t_{-(n-1)} \\ t_1 & t_0 & \cdots & \vdots \\ \vdots & \vdots & \vdots & t_{-1} \\ t_{n-1} & \cdots & t_1 & t_0 \end{bmatrix}$$

Resource-efficient deep learning

- Results: Networks 80 times smaller than original, with ~99.8% of the performance.



Resource-efficient similarity calculation

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- Similarity between objects
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  - Users for recommendations
  - Proteins for disease study

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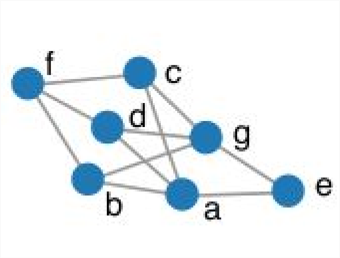
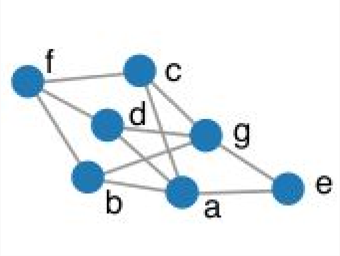
- Generality: Model object and relations in a graph



Görnerup (2015)

Resource-efficient similarity calculation

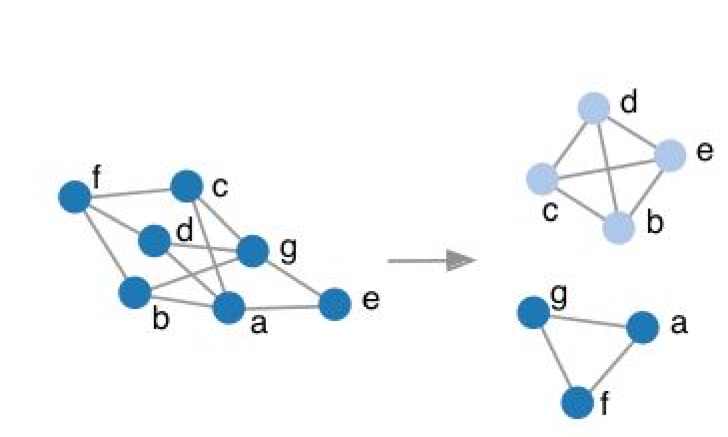
- Similarity between objects
  - Websites for search
  - Users for recommendations
  - Proteins for disease study
- Generality: Model object and relations in a graph
- Problems
  - Too many nodes and connections!
  - Current approaches don't scale!



Görnerup (2015)

Resource-efficient systems

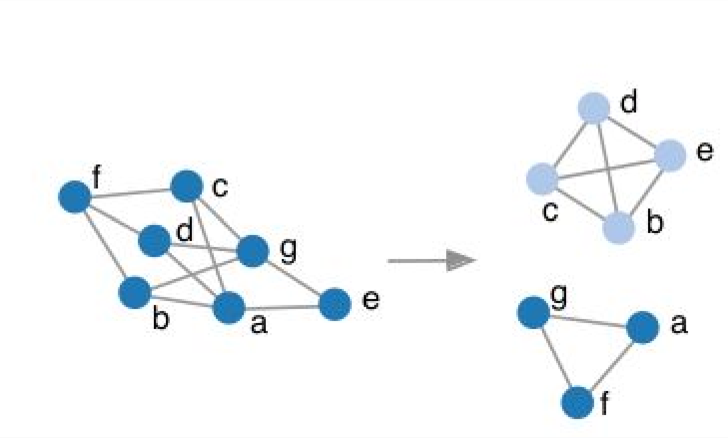
- Idea: Don’t calculate the similarity between Taylor Swift and Beethoven!



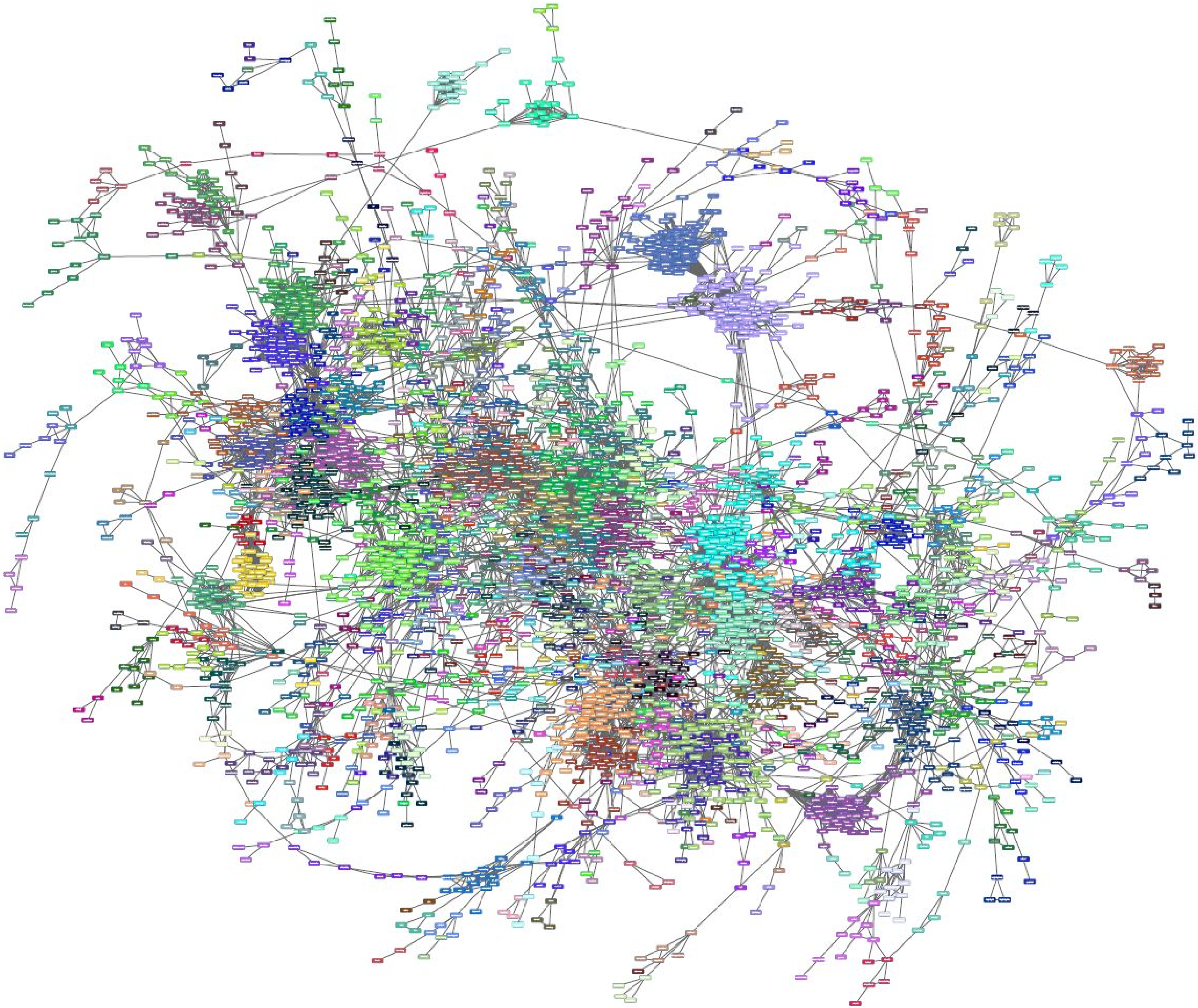
Görnerup (2015)

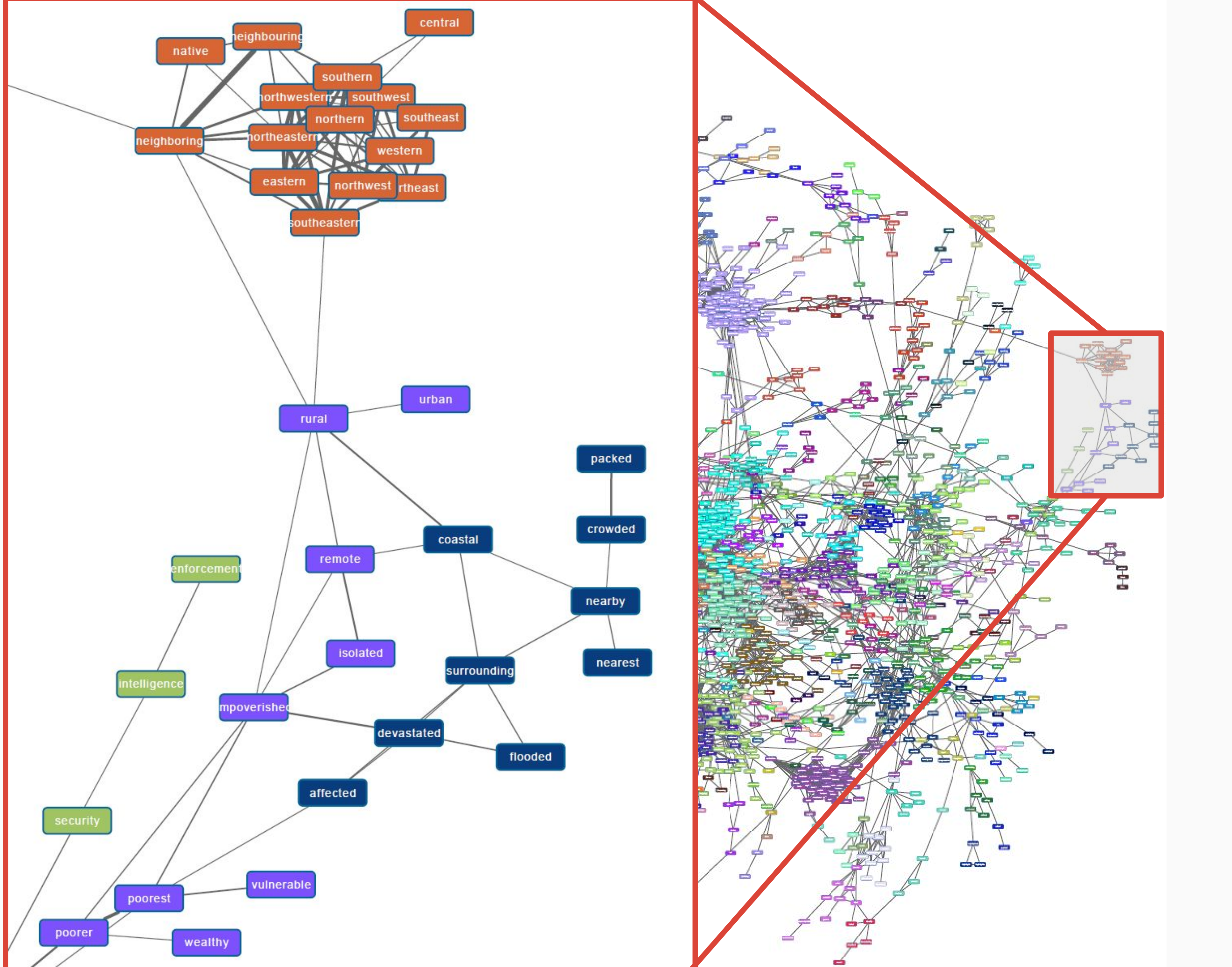
Resource-efficient systems

- Idea: Don't calculate the similarity between Taylor Swift and Beethoven!
- Allows us to tackle orders of magnitude larger graphs!



Görnerup (2015)

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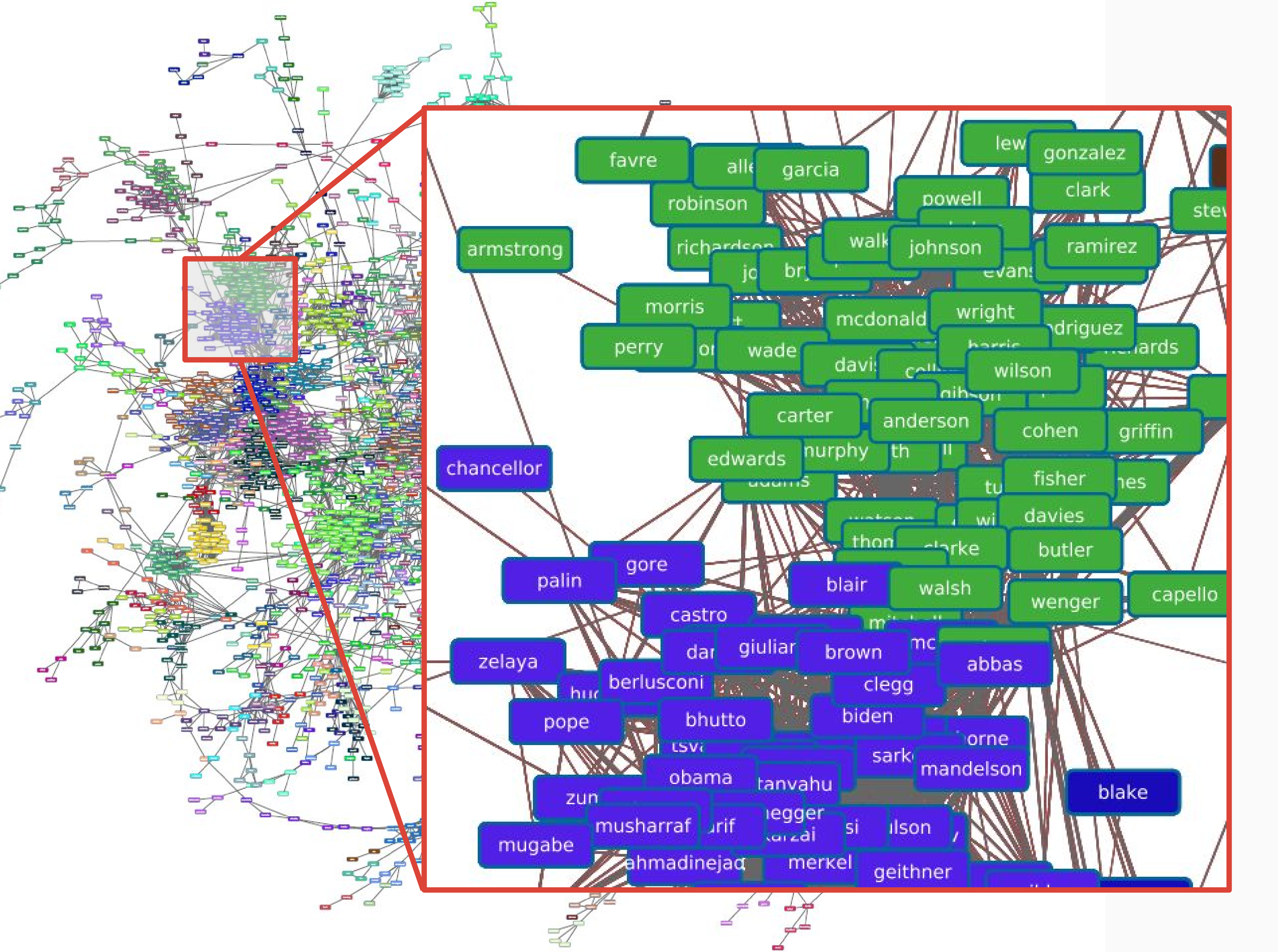
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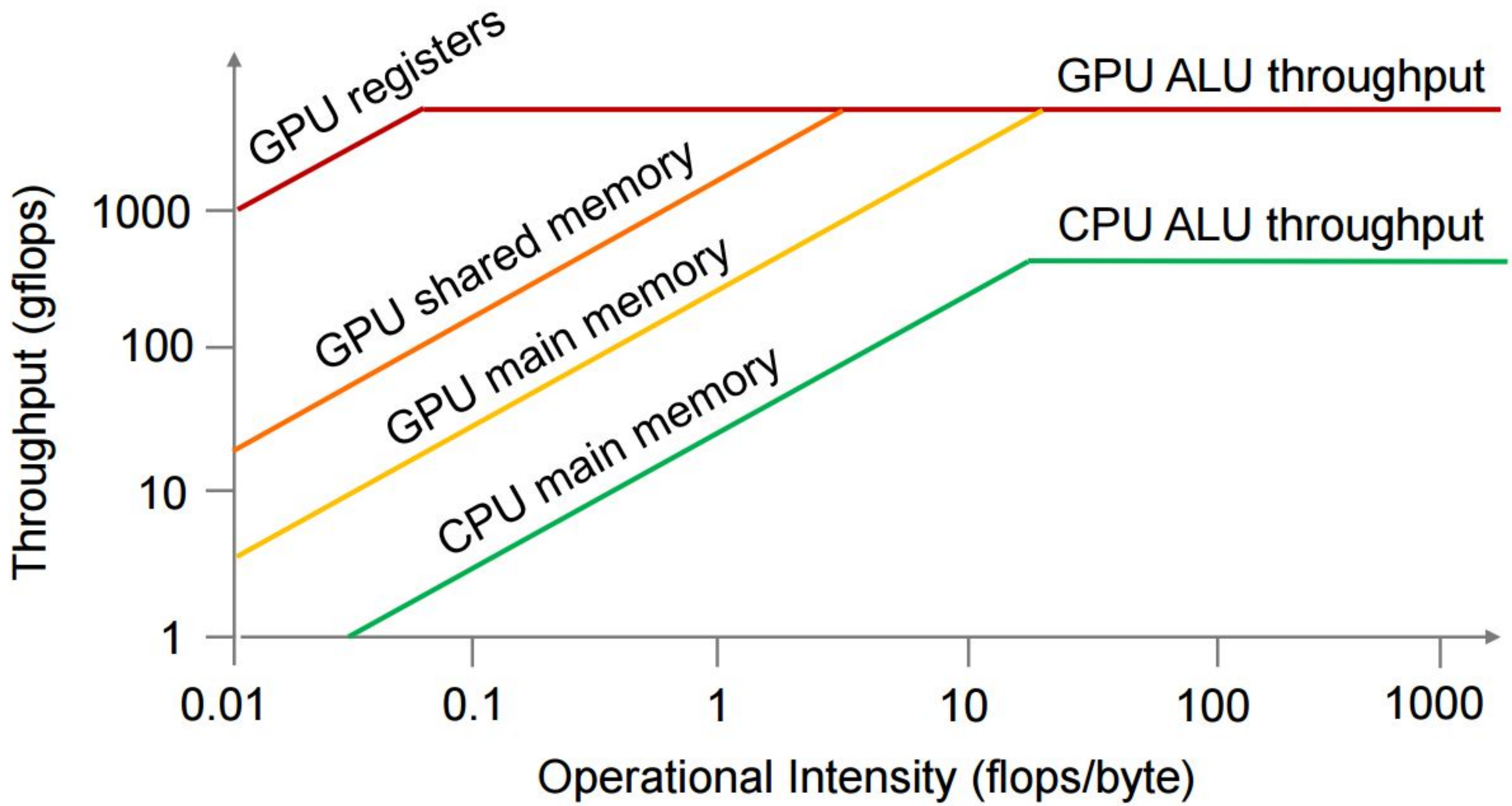
berlusconi
clegg
pope
bhutto
biden
mandelson
obama
blake
musharraf
mugabe
merkel
geithner

Resource efficient systems

BID Data Toolkit

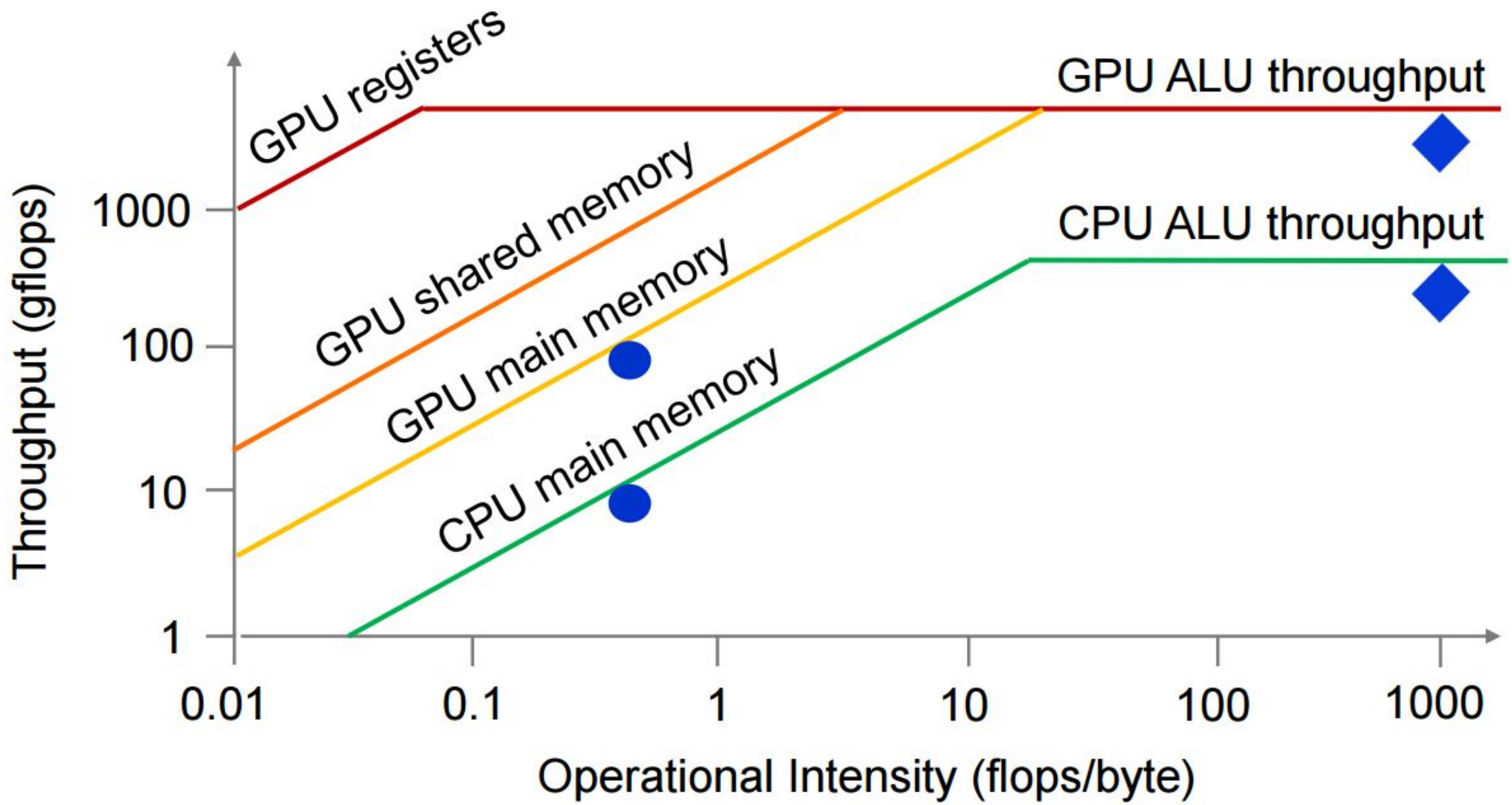
- Canny et al.: *"Big Data Analytics with Small Footprint: Squaring the Cloud"*, KDD 2013
- Canny et al.: *"BIDMach: Large-scale Learning with Zero Memory Allocation"*, NIPS 2013 BigLearn workshop

- Roofline design establishes fundamental performance limits for a computational kernel.



Roofline design

- Dense matrix multiply ◆
- Sparse matrix multiply ●



Roofline design

System	Nodes/cores	Dim	Error	Time (s)	Cost	Energy (KJ)
Graphlab	18/576	100		376	$3.50	10,000
Spark	32/128	100	0.82	146	$0.40	1000
BIDMach	**1**	**100**	**0.83**	**90**	**$0.015**	**20**
Spark	32/128	200	0.82	544	$1.45	3500
BIDMach	**1**	**200**	**0.83**	**129**	**$0.02**	**30**
BIDMach	**1**	**500**	**0.83**	**600**	**$0.10**	**150**

Matrix factorization on the complete Netflix dataset

System	nodes /cores	nclust	Error	Time (s)	Cost	Energy(KJ)
Spark	32/128	256	1.5e13	180	$0.45	1150
BIDMach	**1**	**256**	**1.44e13**	**320**	**$0.06**	**90**
Sk-Learn	1/8	256		3200x4 *	$1.0	10
Spark	96/384	4096	1.05e13	1100	$9.00	22000
BIDMach	**1**	**4096**	**0.995e13**	**735**	**$0.12**	**140**

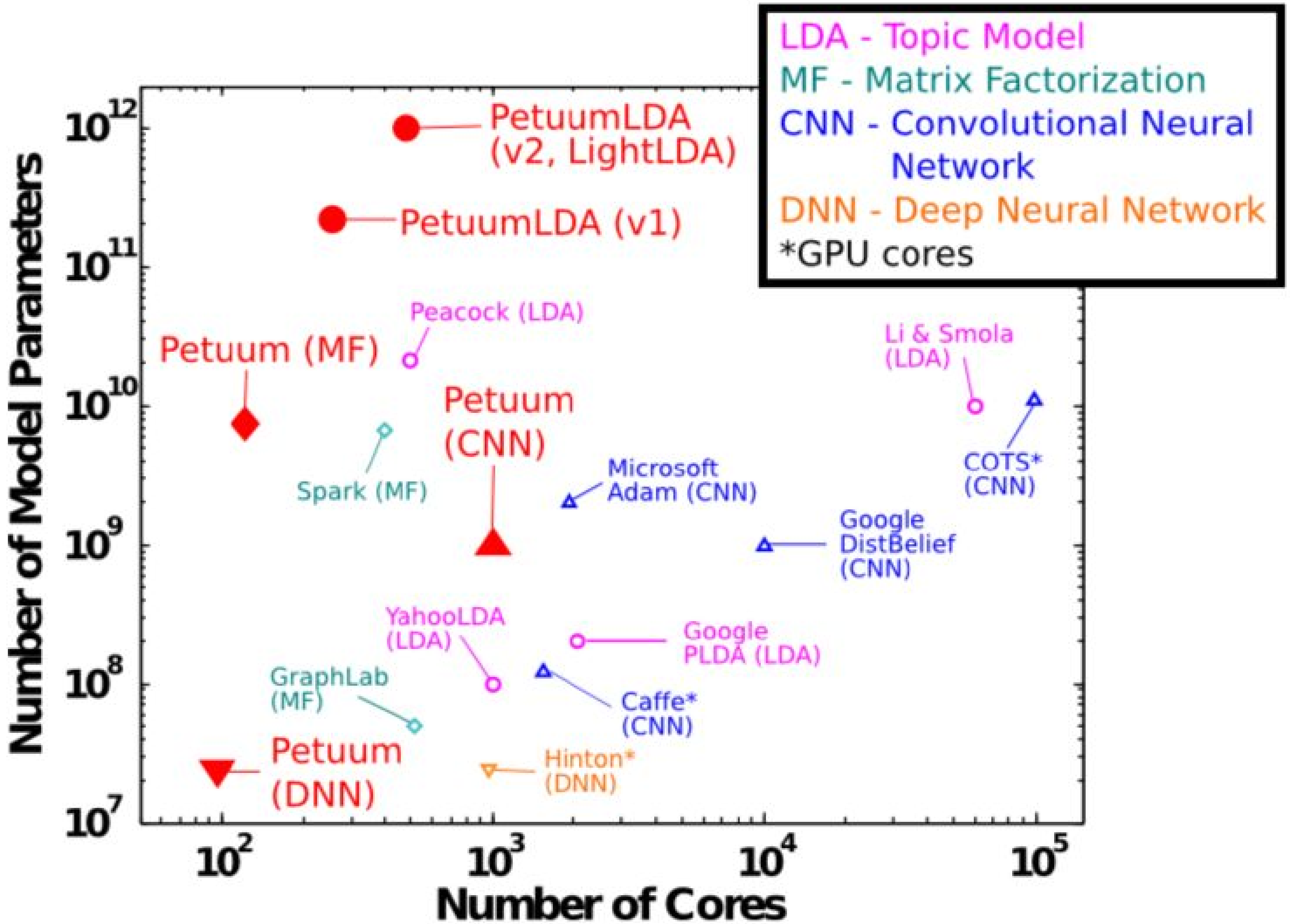
Kmeans on MNIST-8M

Petuum

- Xing et al.: *“Petuum: A New Platform for Distributed Machine Learning on Big Data”*, KDD 2015

Petuum

- Distributed machine learning
- Exploit common properties of ML algorithms to achieve efficient implementation



Source: Xing (2015)

Petuum vs. state of the art (2015)

Takeaway

- Use smart systems and algorithms for large-scale ML
- Don’t need a cluster to do most things

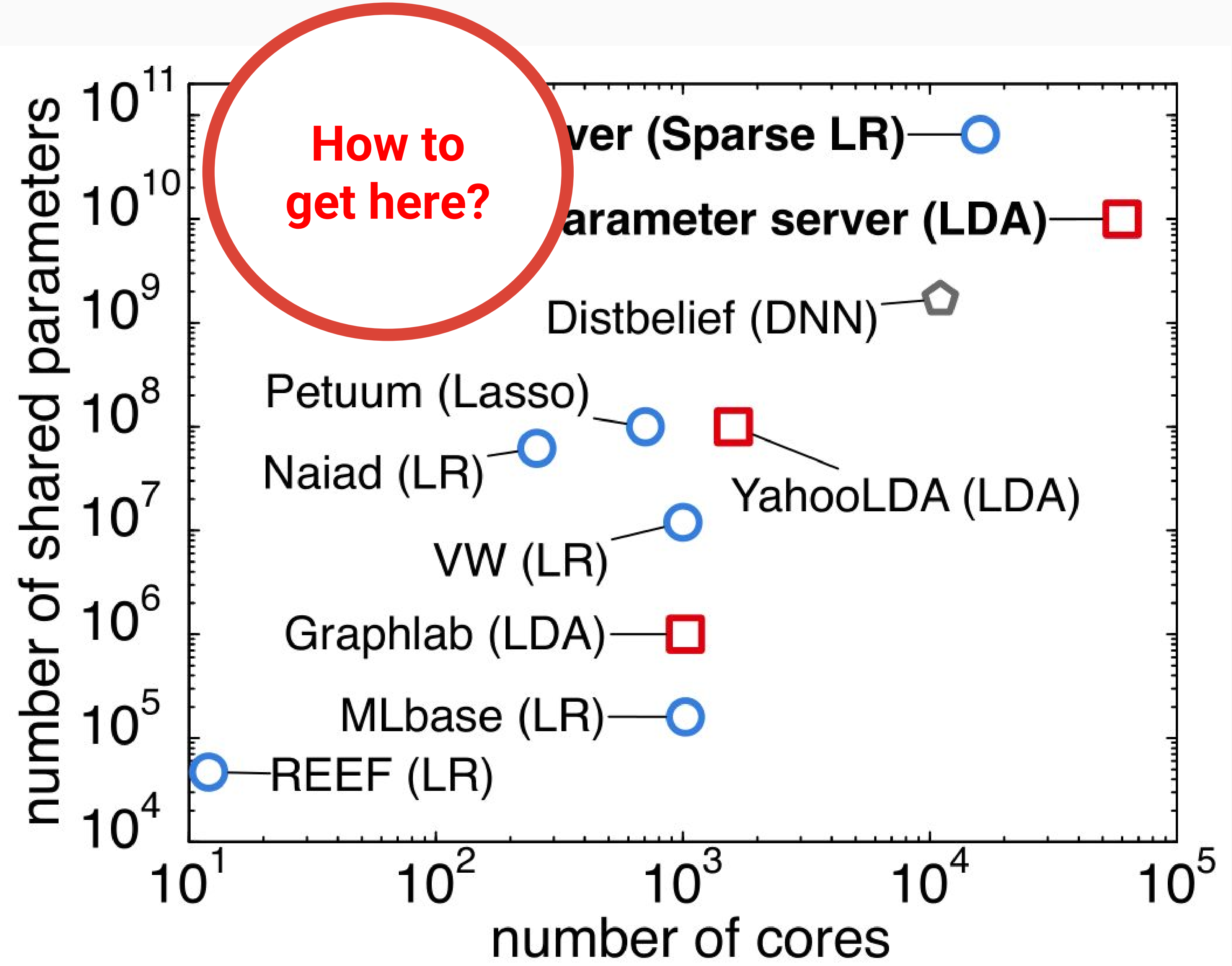
Challenges and research issues

Current issues

- Communication efficient algorithms and systems

Current issues

- Communication efficient algorithms and systems
- Resource efficient algorithms and systems



Active research area

Future issues

- Integrated systems and ML research: “Symbiotic” systems and algorithms
    - How can we further take advantage of ML program properties to build better systems?
    - How can we reconcile view of “ML people” and “systems people” to achieve progress on both sides?

Future issues

- “Symbiotic” systems and algorithms research
- Streaming/online learning

Future issues

- “Symbiotic” systems and algorithms research
- Streaming/online learning
- Exascale ML

Thank You.

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References

- Silver (2016): Mastering the game of Go with deep neural networks and tree search
- Karpathy: CS231n Course material
- Dolhansky: Artificial Neural Networks Blog post series
- Champandard (2016): Semantic Style Transfer and Turning Two-Bit Doodles into Fine Artwork
- Görnerup (2015): Knowing an Object by the Company it Keeps: A Domain-Agnostic Scheme for Similarity Discovery
- BID Data Toolkit: BID Data Project Website
- CMU Petuum: Petuum Project

Other references found in the text.