Graph Neural Networks

Network Application Diagnostics
B2M32DSAA

Radek Mařík

Czech Technical University
Faculty of Electrical Engineering
Department of Telecommunication Engineering
Prague CZ

November 18, 2025

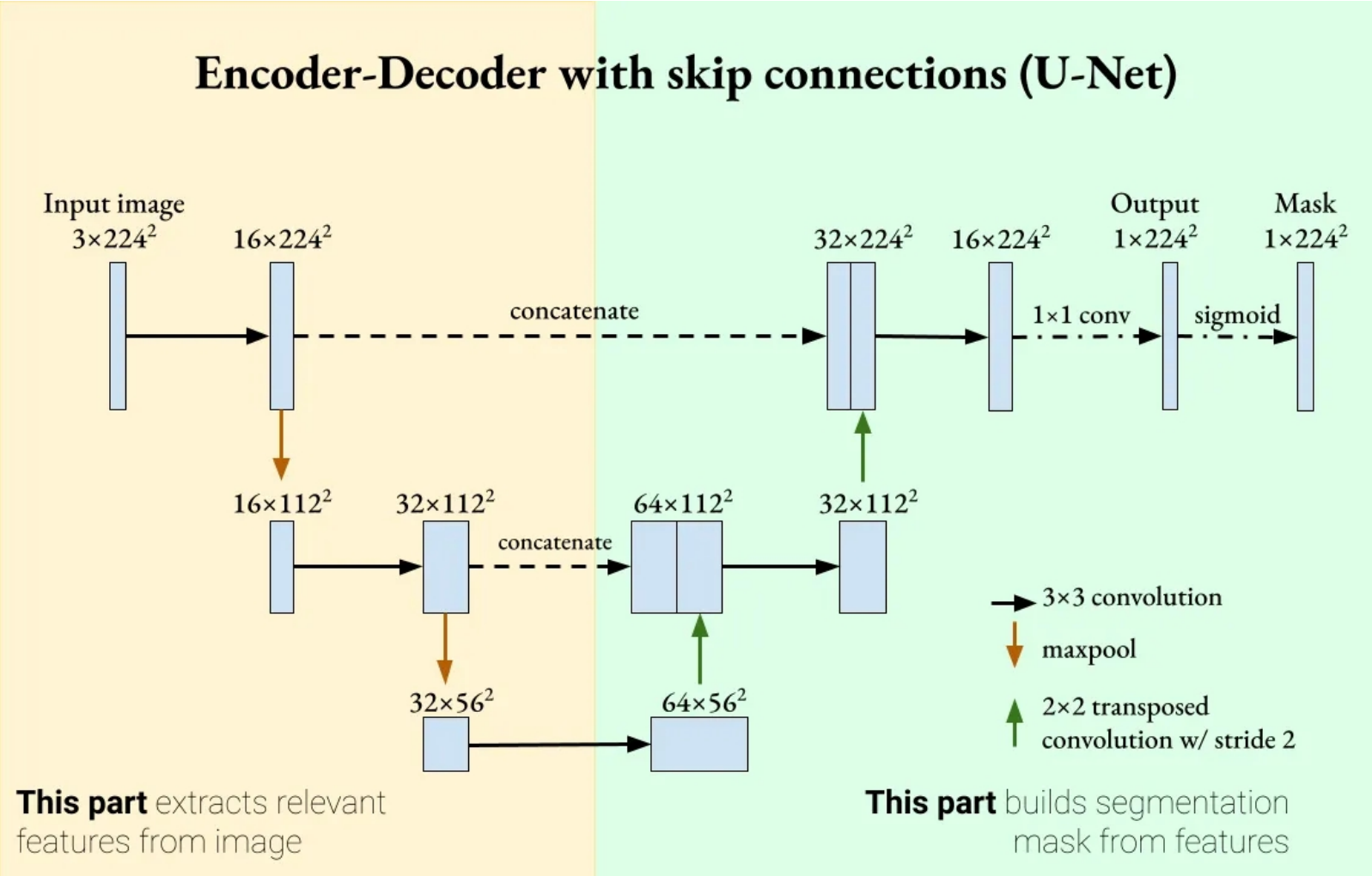
Outline

1. Deep Learning
   - Advanced Neural Networks
2. Network Inference
   - Introduction
   - Network Inference Example - Viber
   - Graph Neural Network (GNN)
3. Natural Language Processing (NLP)
   - Embeddings and Neural Network Architectures

Outline

1. Deep Learning
   - Advanced Neural Networks
2. Network Inference
   - Introduction
   - Network Inference Example - Viber
   - Graph Neural Network (GNN)
3. Natural Language Processing (NLP)
   - Embeddings and Neural Network Architectures

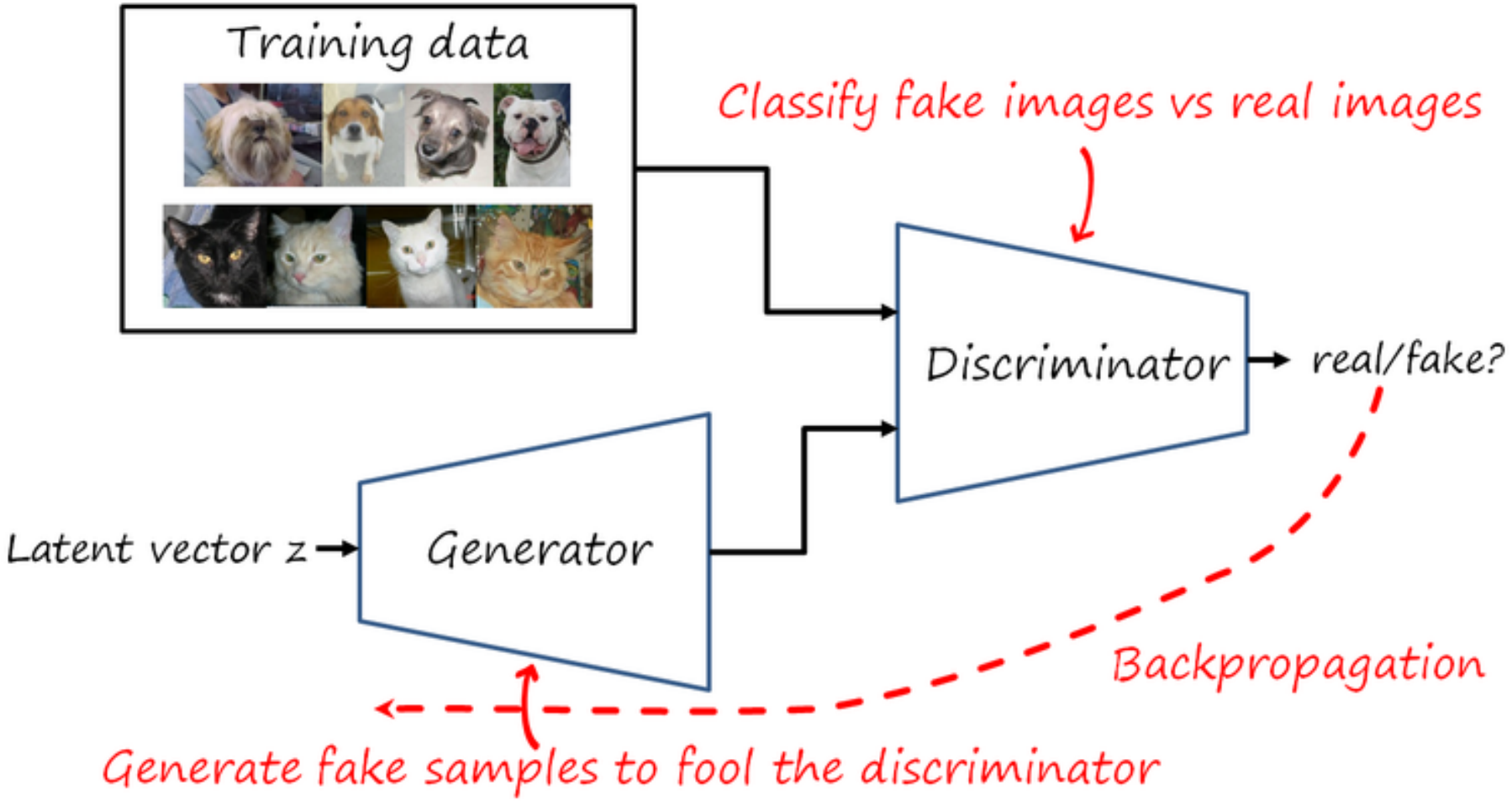
UNet Neural Network (CRAFT [BLH+19])



Used in computer vision in segmentation.

https://towardsdatascience.com/understanding-u-net-61276b10f360

Generative adversarial networks (GANs) (2014)



Wasserstein GAN (2017)

http://www.lherranz.org/2018/08/07/imagetranslation/

Fake Image Generation (2018)

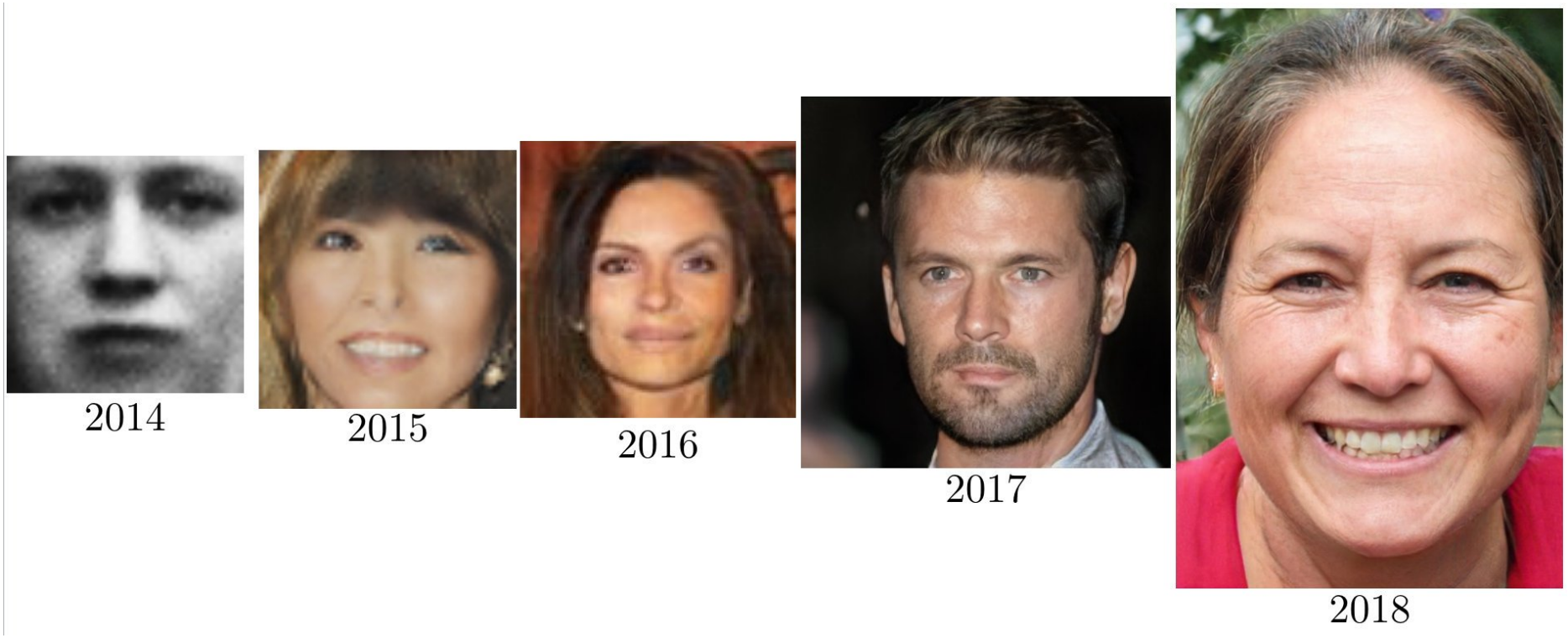
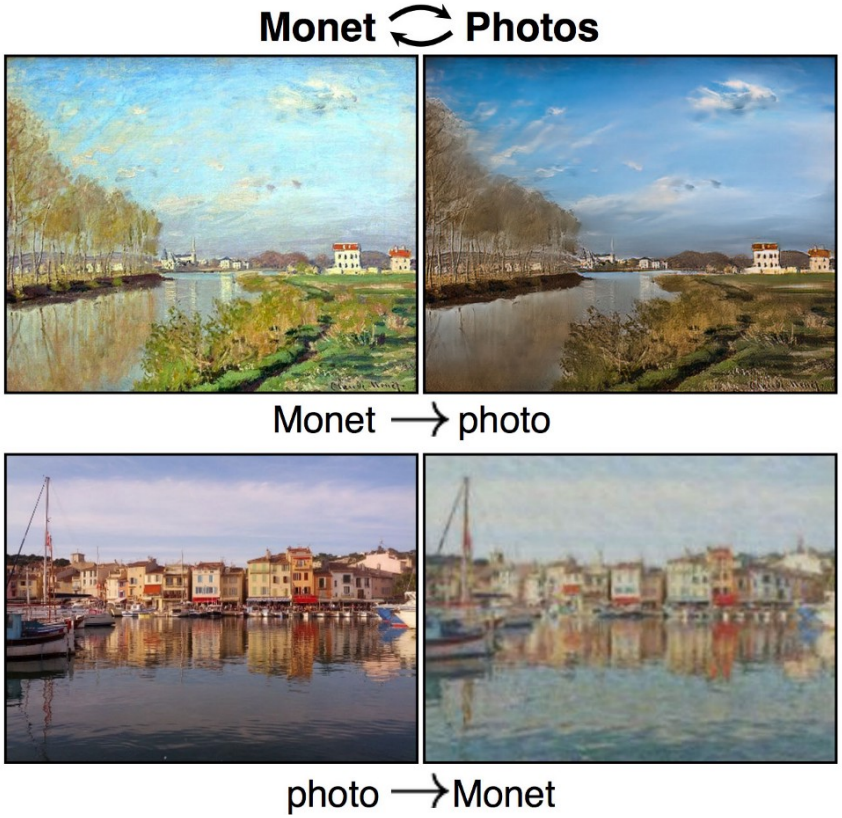


Image Style Conversion - CycleGAN (2017) [ZPIE17]



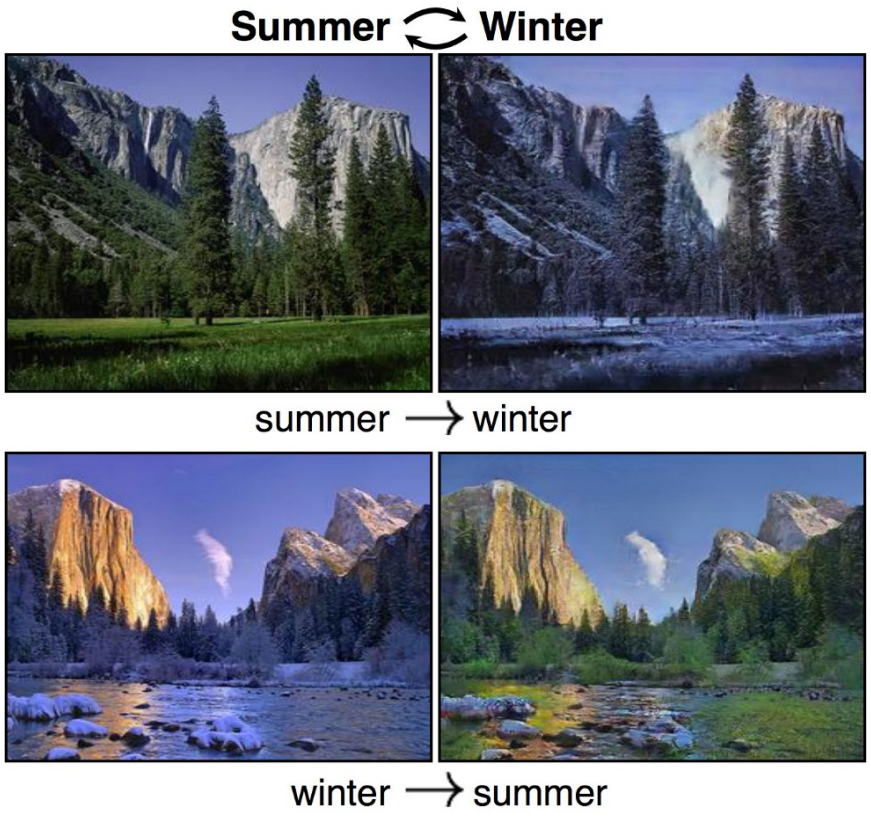


Image Style Conversion Failures (2017) [ZPIE17]

Outline

1. Deep Learning
   - Advanced Neural Networks
2. Network Inference
   - Introduction
   - Network Inference Example - Viber
   - Graph Neural Network (GNN)
3. Natural Language Processing (NLP)
   - Embeddings and Neural Network Architectures

Network Topology Inference [Kol09]

- What should constitute a vertex and an edge is determined by user-specified decisions and rules.
- Such a network graph construction lacks an element of validation.
  - if the network representation is "accurate",
    - i.e. capturing some well-defined but unobservable relational structure.
  - What accuracy can be expected given the available measurements?
  - Are there other similar representations with about the same accuracy?
  - How is the representation robust to changes in the measurements?
  - How is the representation usefull for other purposes?

Network Topology Inference Problem

- Given a set of measurements from a system of interest, e.g.
  - vertex attributes $\boldsymbol{x} = (x_1, \ldots, x_{N_\mathcal{V}})$
  - binary indicators $\boldsymbol{y} = [y_{ij}]$ of certain edges.
- and given a collection $\mathscr{G}$ of potential graphs G,
- select an appropriate member of $\mathscr{G}$ that best captures the underlying state of the system.

Network Topology Inference [Kol09]

- What should constitute a vertex and an edge is determined by user-specified decisions and rules.
- Such a network graph construction lacks an element of validation.
  - if the network representation is "accurate",
    - i.e. capturing some well-defined but unobservable relational structure.
  - What accuracy can be expected given the available measurements?
  - Are there other similar representations with about the same accuracy?
  - How is the representation robust to changes in the measurements?
  - How is the representation usefull for other purposes?

Network Topology Inference Problem

- Given a set of measurements from a system of interest, e.g.
  - vertex attributes $\boldsymbol{x} = (x_1, \ldots, x_{N_\mathcal{V}})$
  - binary indicators $\boldsymbol{y} = [y_{ij}]$ of certain edges.
- and given a collection $\mathscr{G}$ of potential graphs G,
- select an appropriate member of $\mathscr{G}$ that best captures the underlying state of the system.

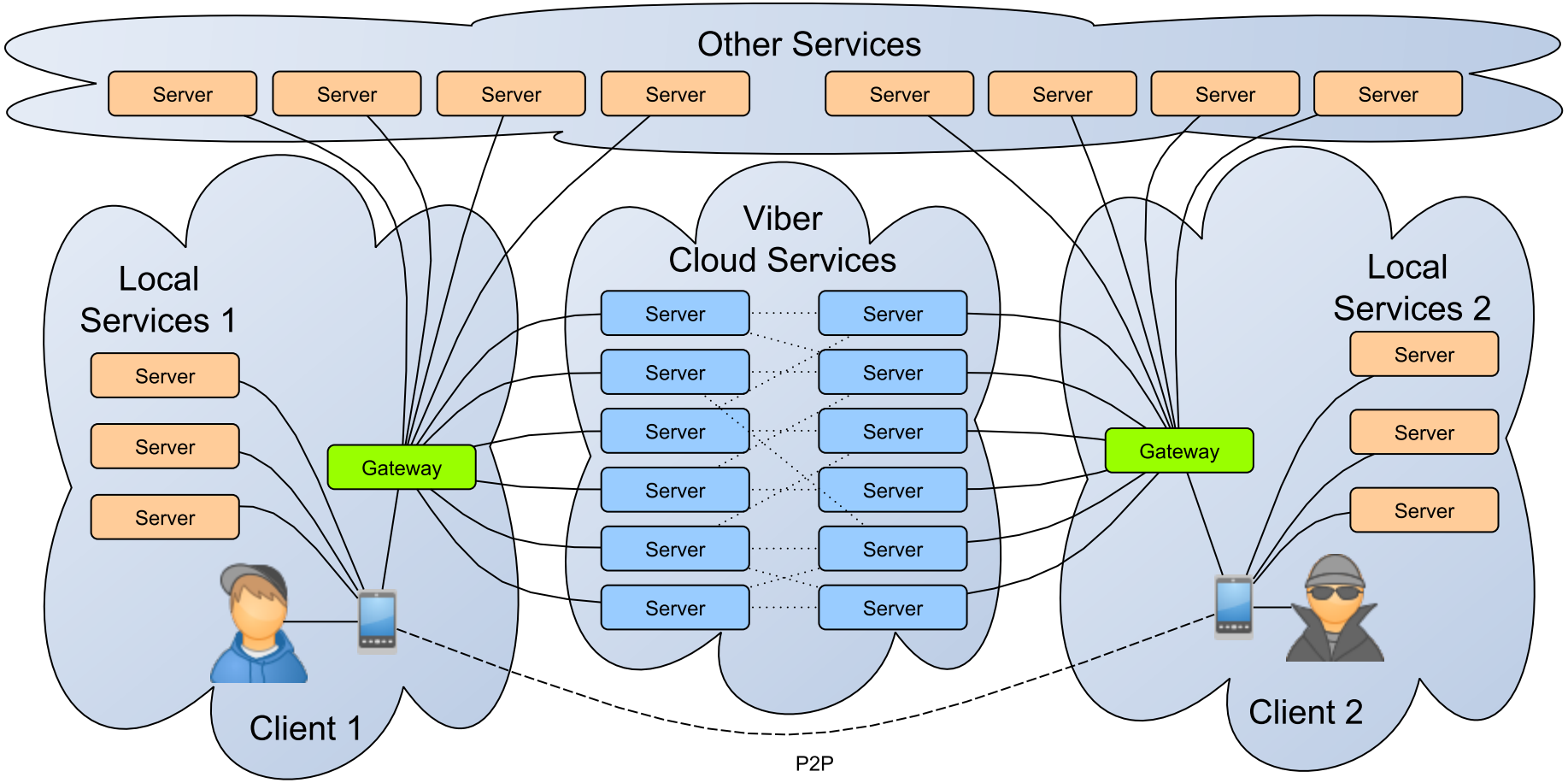
Network Inference Problems [Kol09]

- **Link Prediction** . . . inferring whether or not a pair of vertices does or does not have an edge between them
  - using measurements that include a subset of vertex pairs whose edge/non-edge status is already observed.
  - knowledge of all of the vertices.
  - the status of some of the edges/non-edges
- **Association Graph Inference** . . . the relation defining edges is itself unobserved and must be inferred from measurements reflecting these characteristics.
  - no knowledge of edge status anywhere in the network graph,
  - relevant measurements at all of the vertices are assumed.
- **Tomographic Network Inference** . . . the measurements are available only at vertices that are somehow at the perimeter of the network.
  - measurements at only a particular subset of vertices are known.

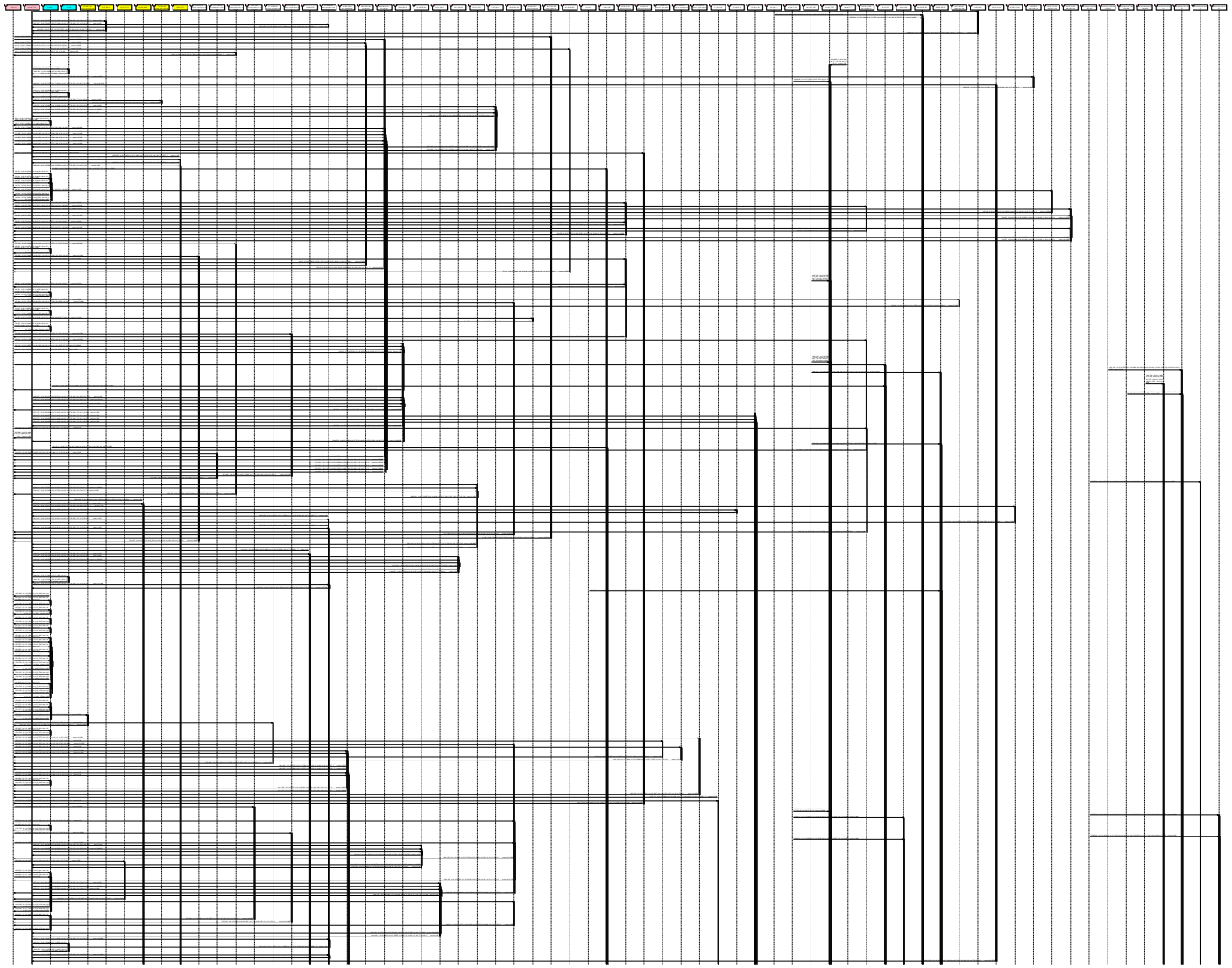
Outline

1. Deep Learning
   - Advanced Neural Networks
2. Network Inference
   - Introduction
   - Network Inference Example - Viber
   - Graph Neural Network (GNN)
3. Natural Language Processing (NLP)
   - Embeddings and Neural Network Architectures

Exemplar (Viber) Environment [MBKK15]



Example Capture Characteristics [MBKK15]

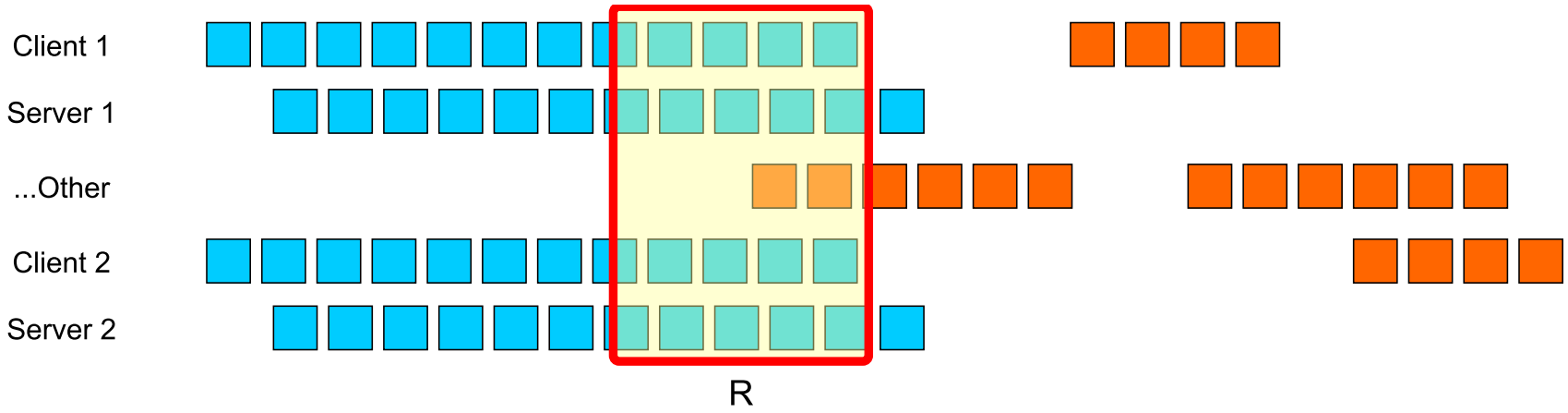


- 138882 PCAP blocks
- 1788 transport sessions
- 2 clients
- 22 viber.com servers
- 150 peers of 2 clients
- 5660 possible concurrent sessions
- How to analyze?

Concurrent Communication Detection [MBKK15]

Selection of IP nodes

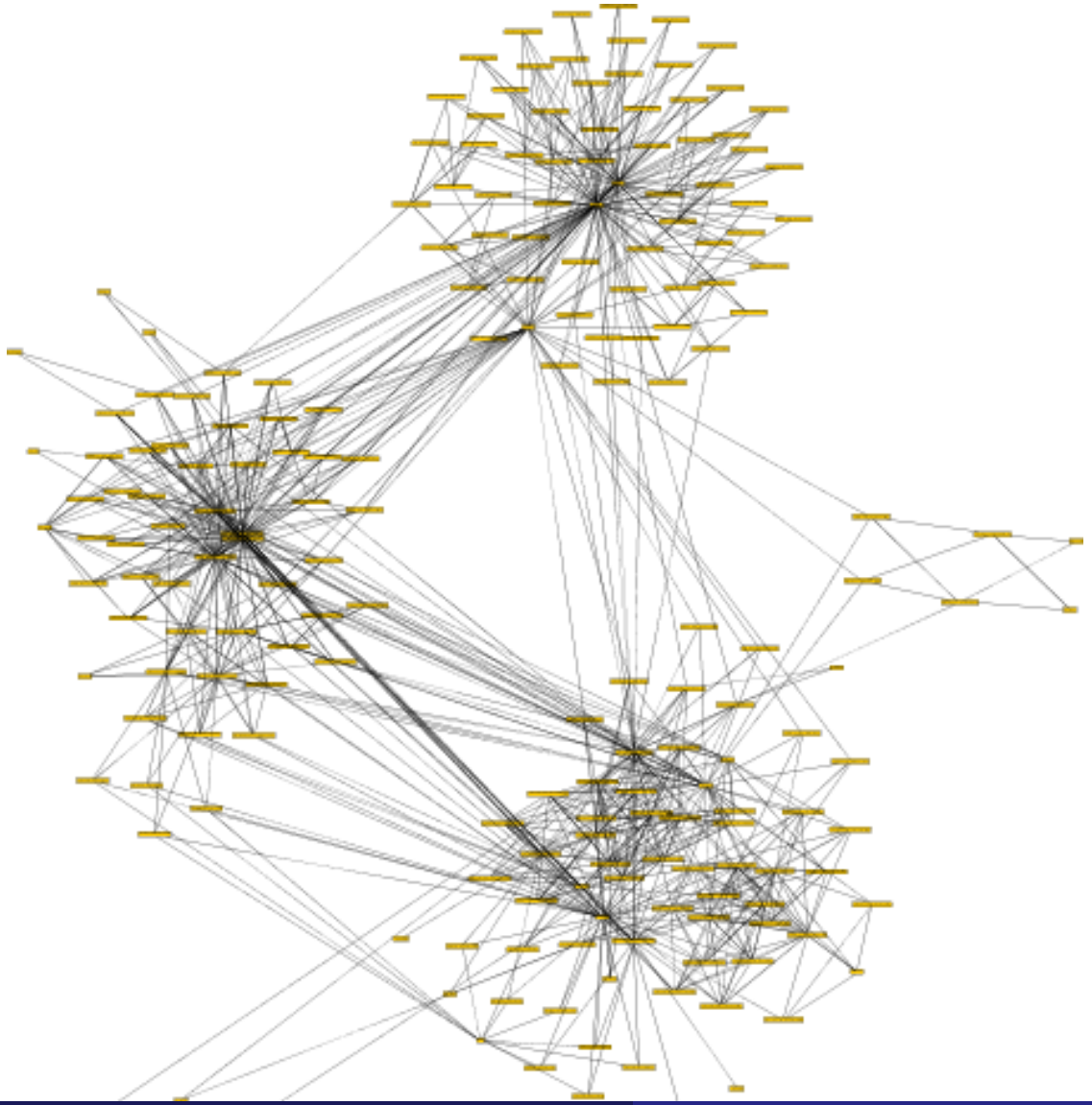
- *viber.com* servers → viber clients → other Viber servers
- classified based on entropy based characteristics of TCP/IP distributions



$$s(a,b) = \frac{\sum_{\forall i,j: t_a[i]-t_b[j]<R} R/(t_a[i]-t_b[j])}{\sum_{\forall i,j: t_a[i]-t_b[j]<R} 1}$$

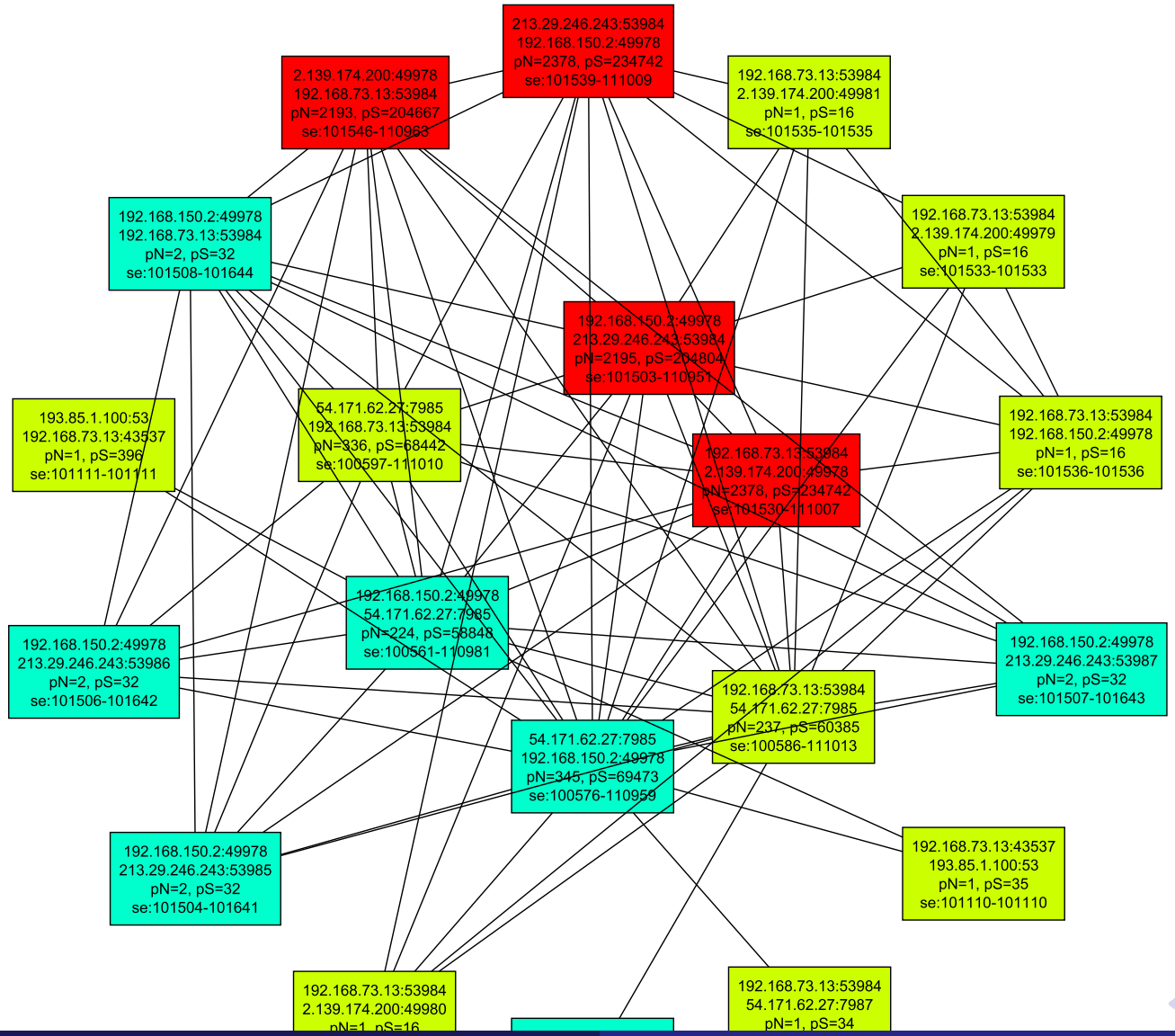
In our experiments: $R = 50ms, \quad s(a,b) > 0.001$

UDP packet sequence concurrency as a complex network [MBKK15]



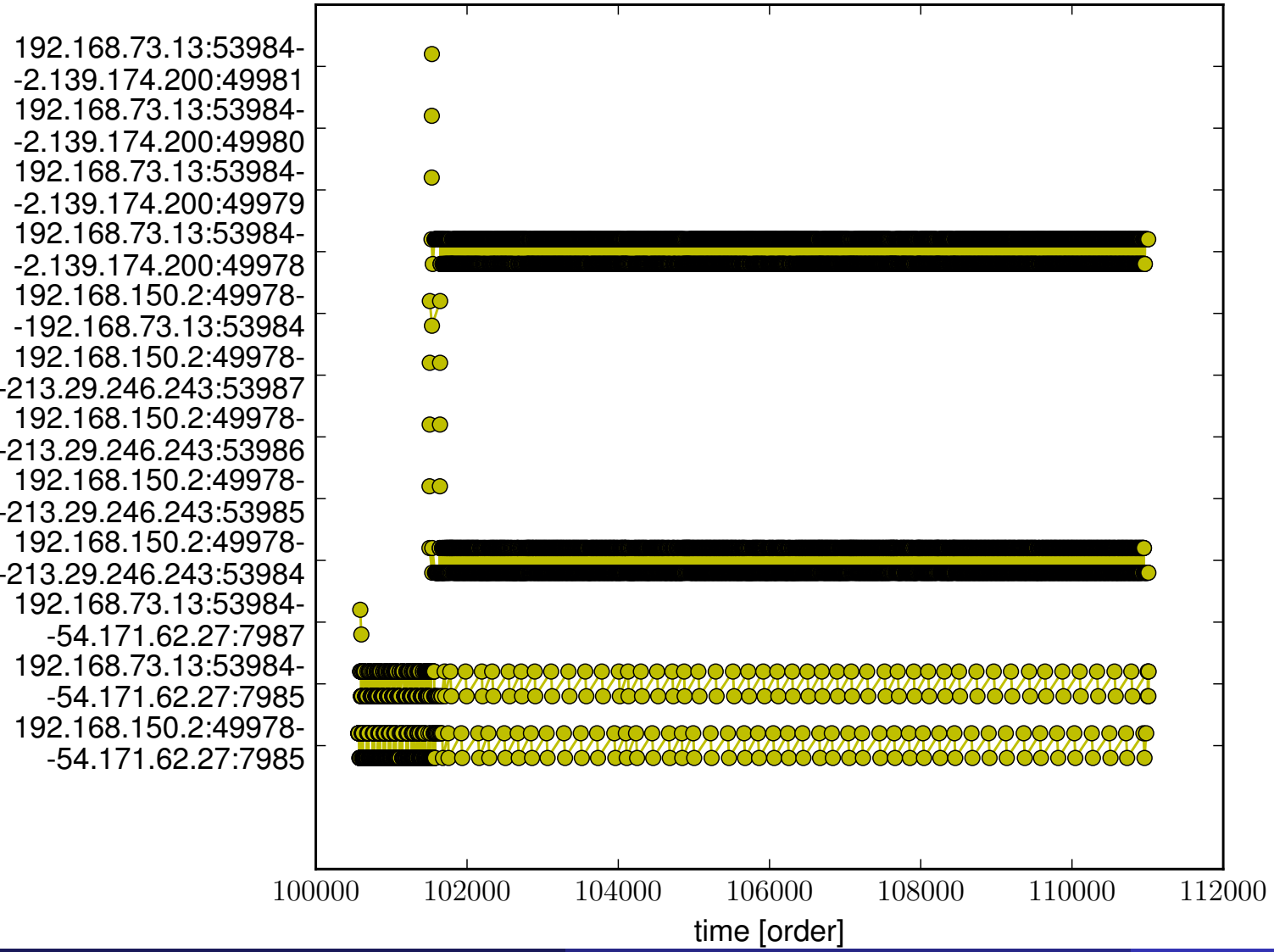
- captures with two clients
- *"communities"* of concurrent sessions
- some clusters related to only one client
- interesting clusters consist of nodes of both clients

UDP packet sequence concurrency network component [MBKK15]



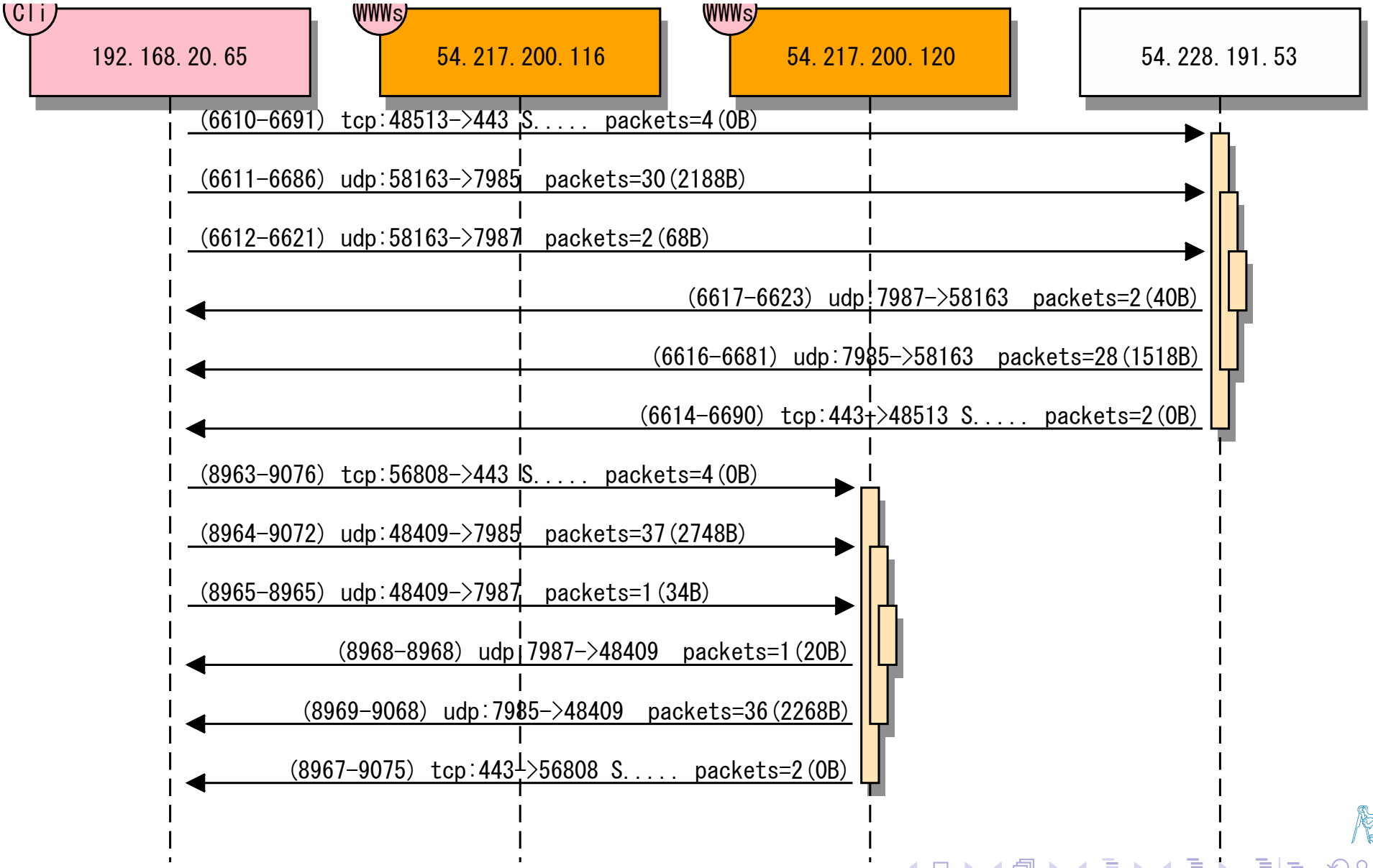
- restricted on one of the components
- two *Viber* clients
- 192.168.73.13
- 192.168.150.2

UDP packet sequence concurrency - packet timing [MBKK15]

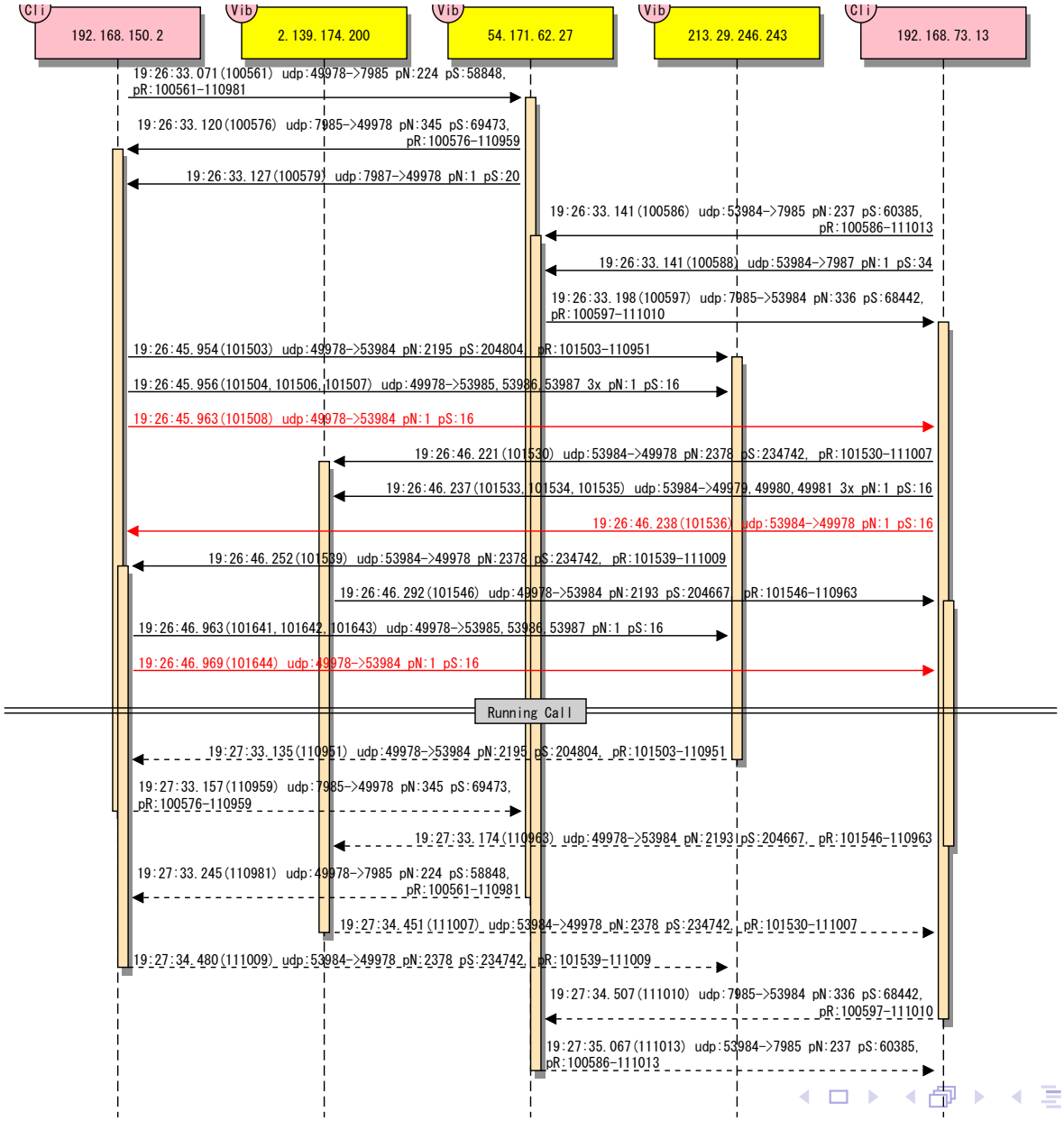


- signals
- calls
- keep-alive packets
- direct client to client packets

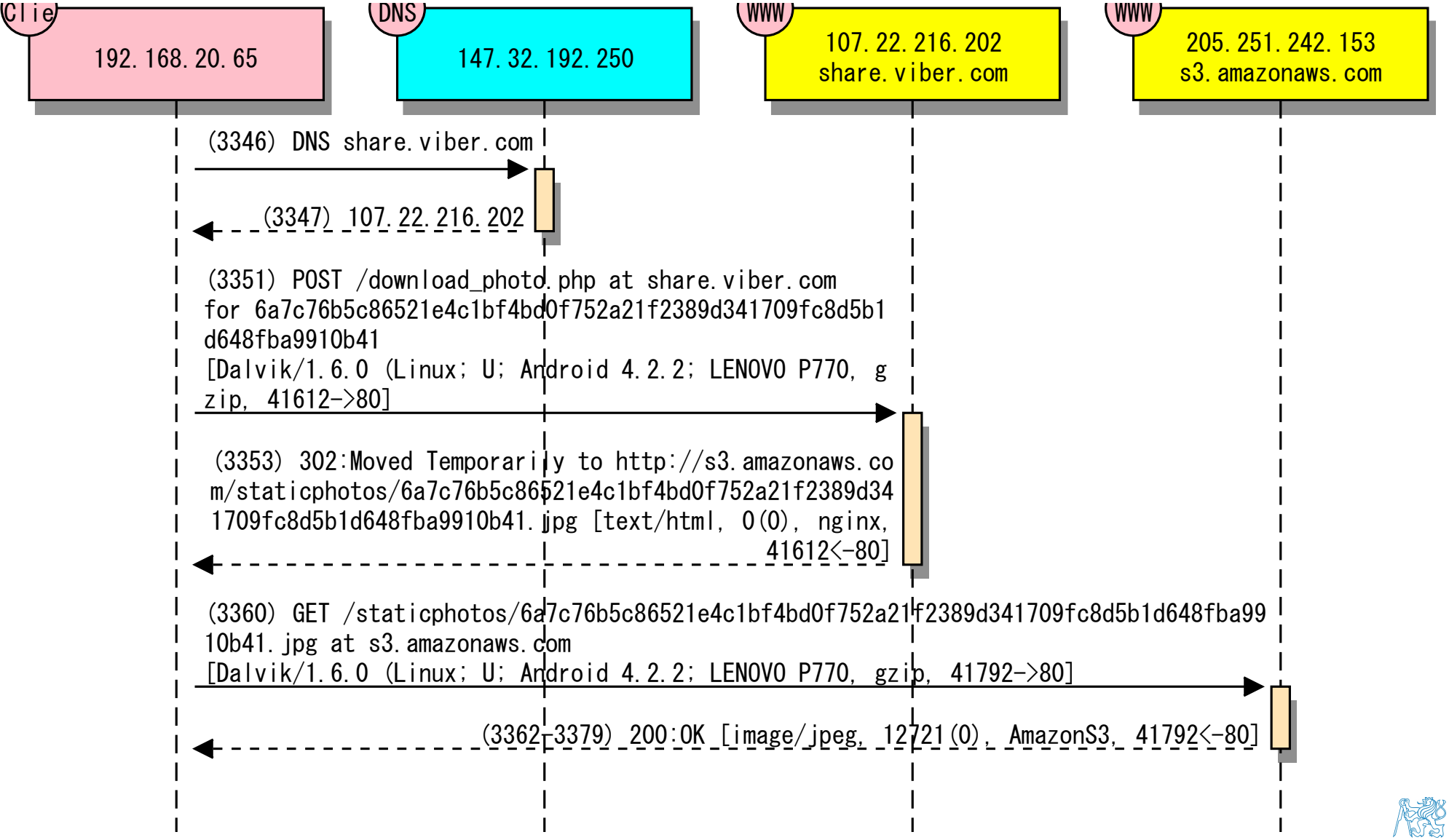
Message Sending [MBKK15]



Voice Call [MBKK15]



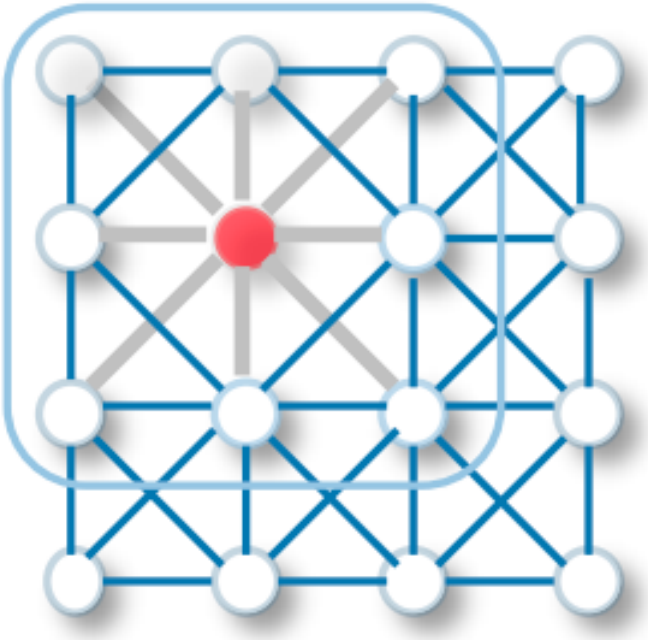
Security/Privacy Assessment - Contact Picture Transfer

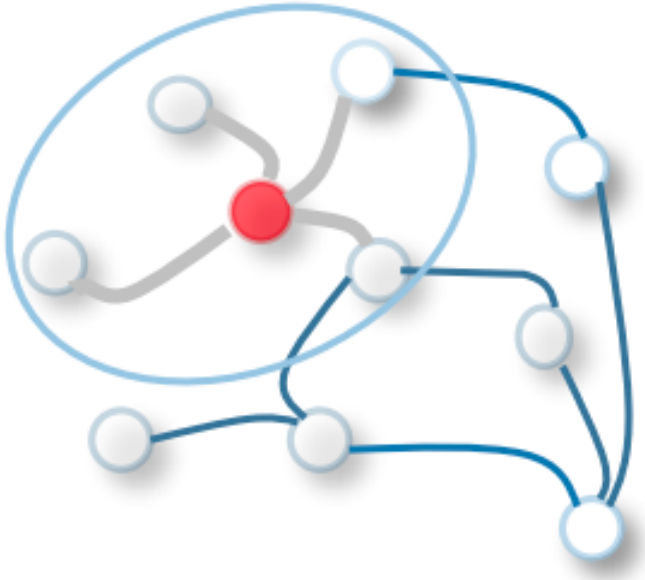


Outline

1. Deep Learning
   - Advanced Neural Networks
2. Network Inference
   - Introduction
   - Network Inference Example - Viber
   - Graph Neural Network (GNN)
3. Natural Language Processing (NLP)
   - Embeddings and Neural Network Architectures

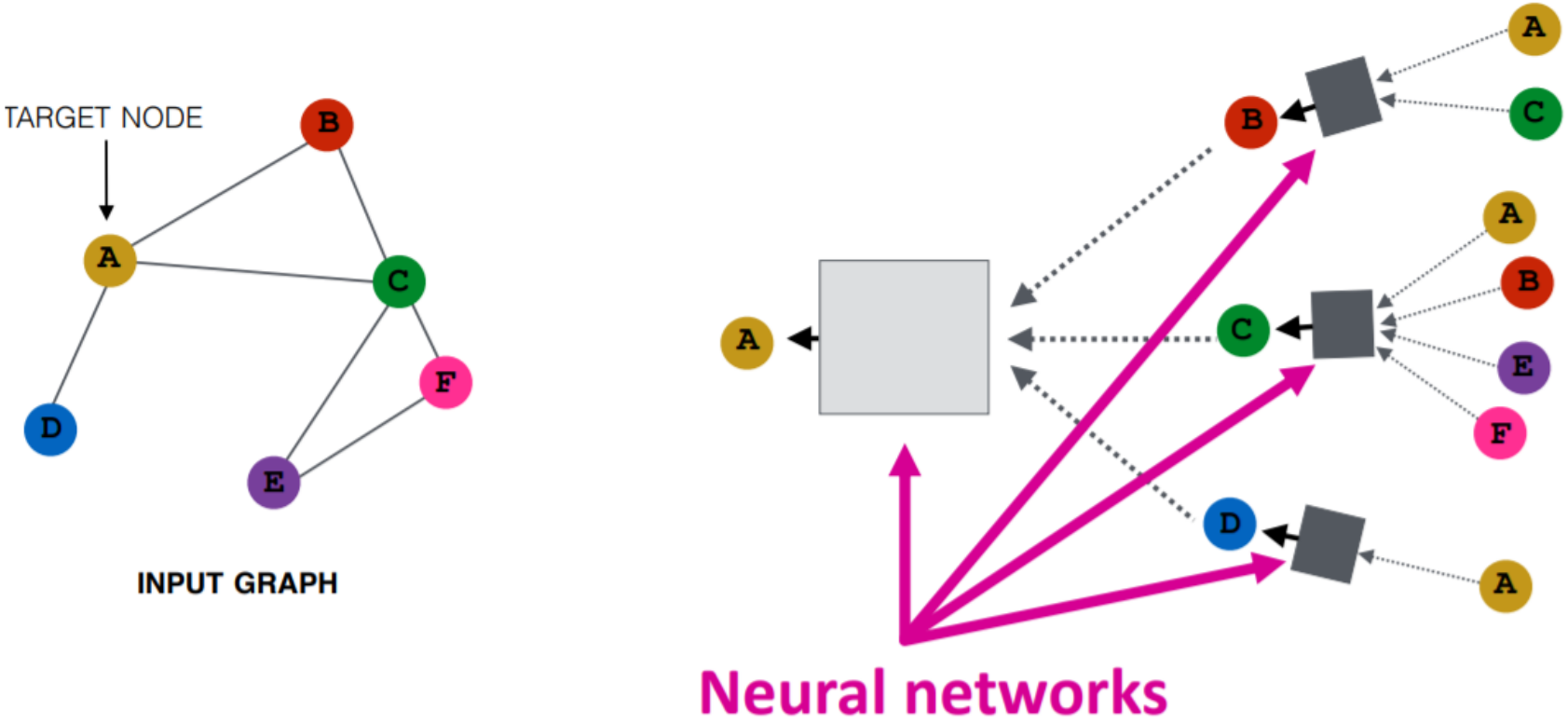
Graph Neural Network Concept





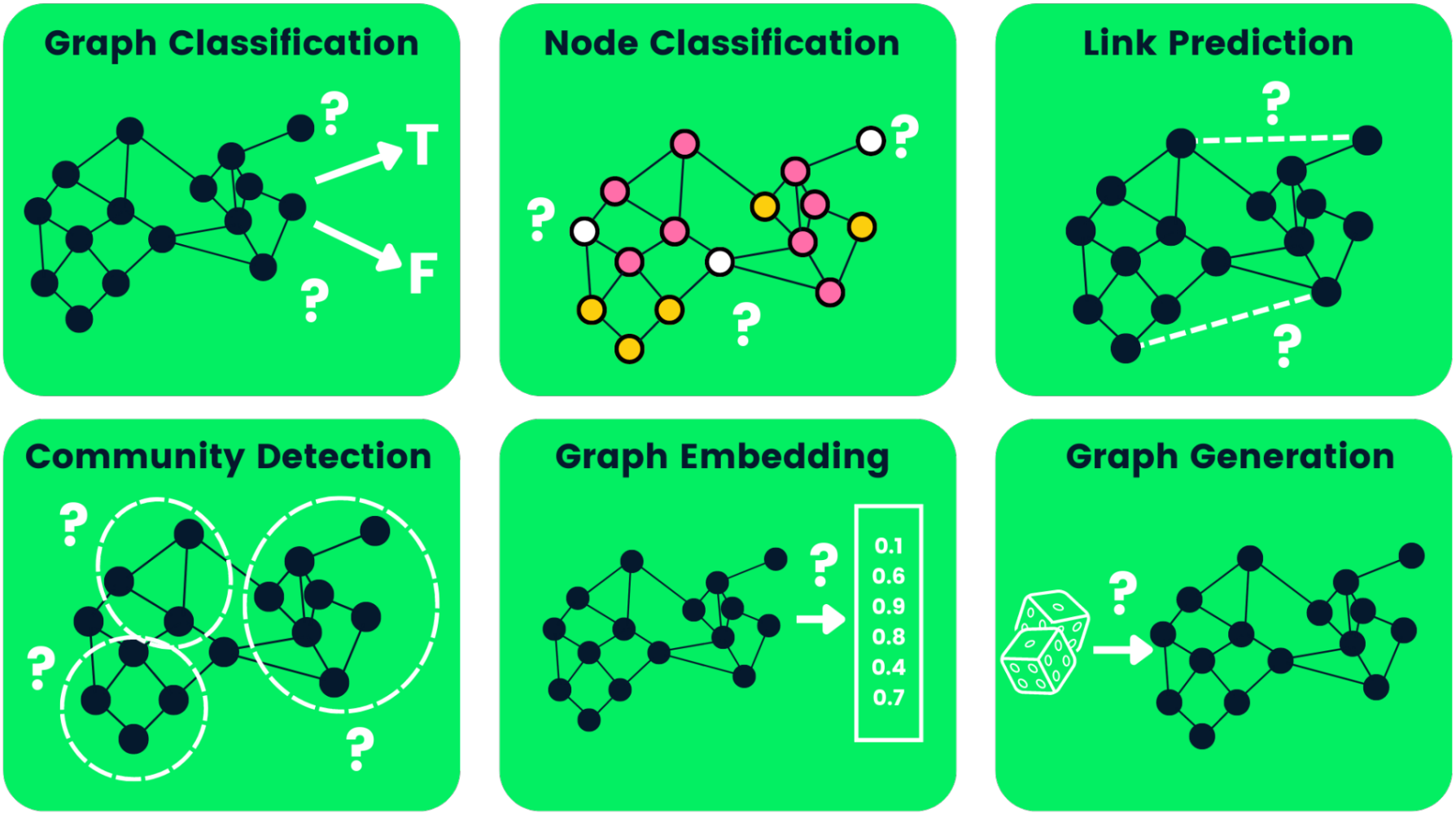
https://www.datacamp.com/tutorial/comprehensive-introduction-graph-neural-networks-gnns-tutorial

Graph Message Passing



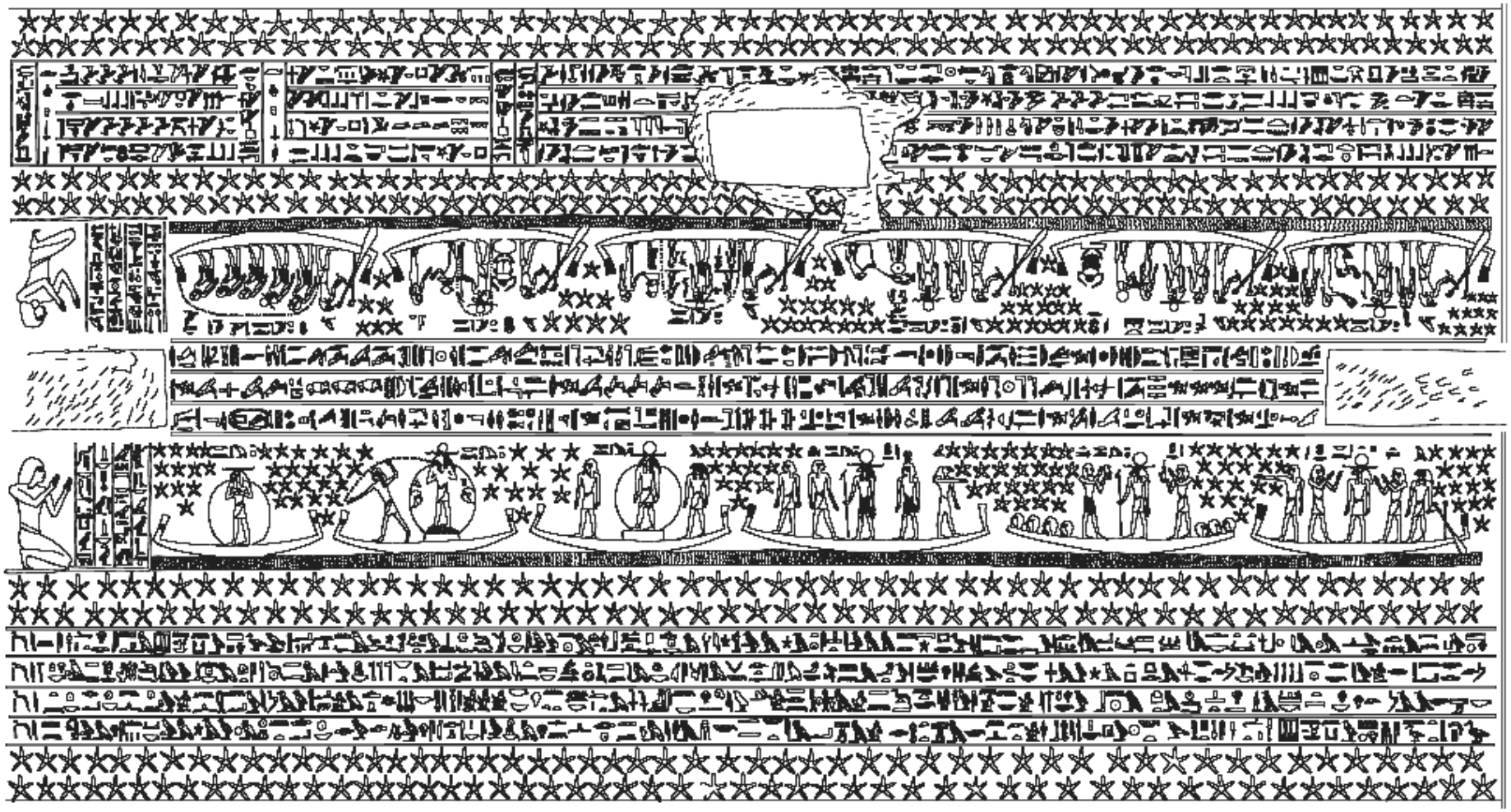
http://web.stanford.edu/class/cs224w/slides/06-GNN1.pdf

GNN Problems

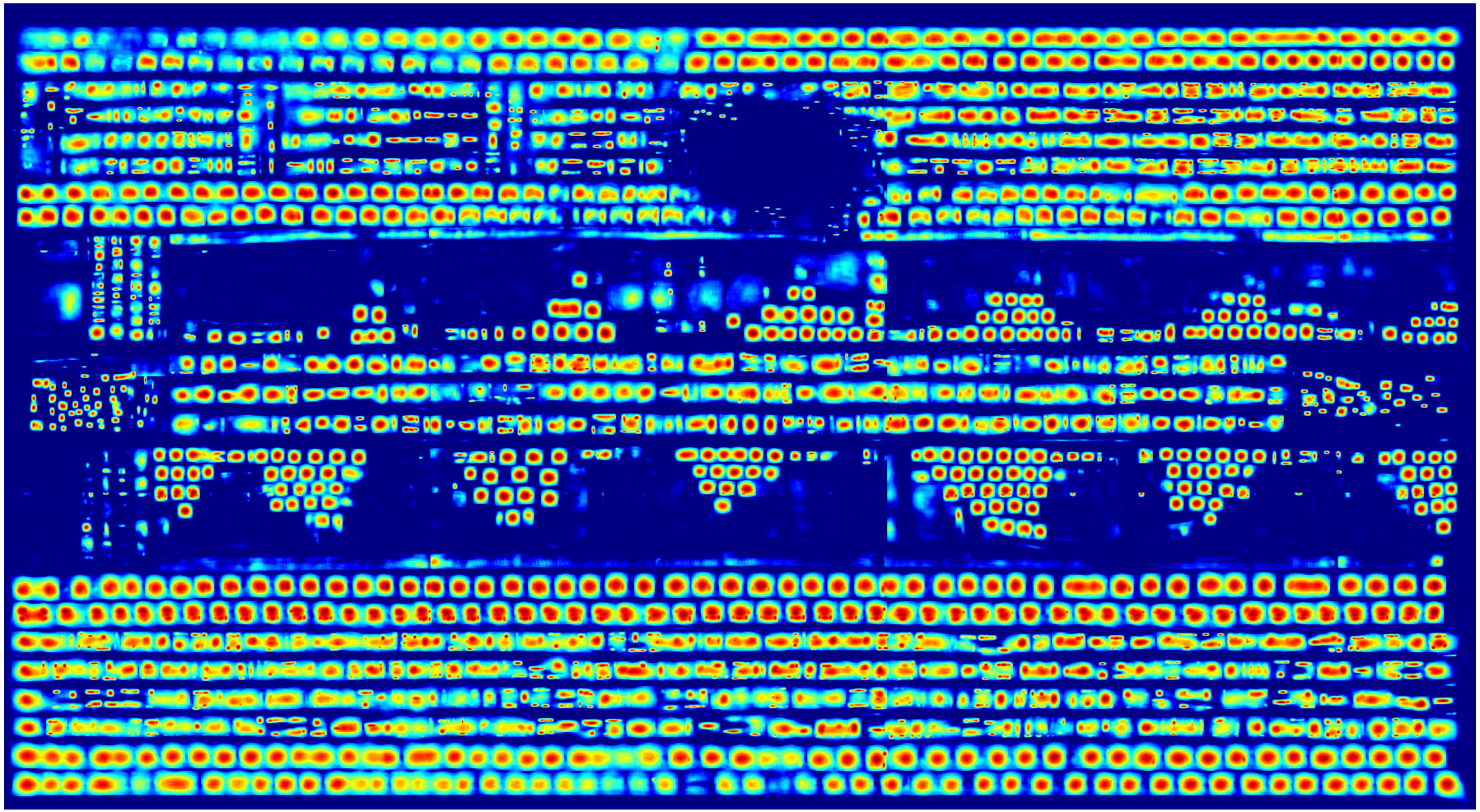


https://www.datacamp.com/tutorial/comprehensive-introduction-graph-neural-networks-gnns-tutorial

Input Dataset - Facsmiles with Hieroglyfic Texts

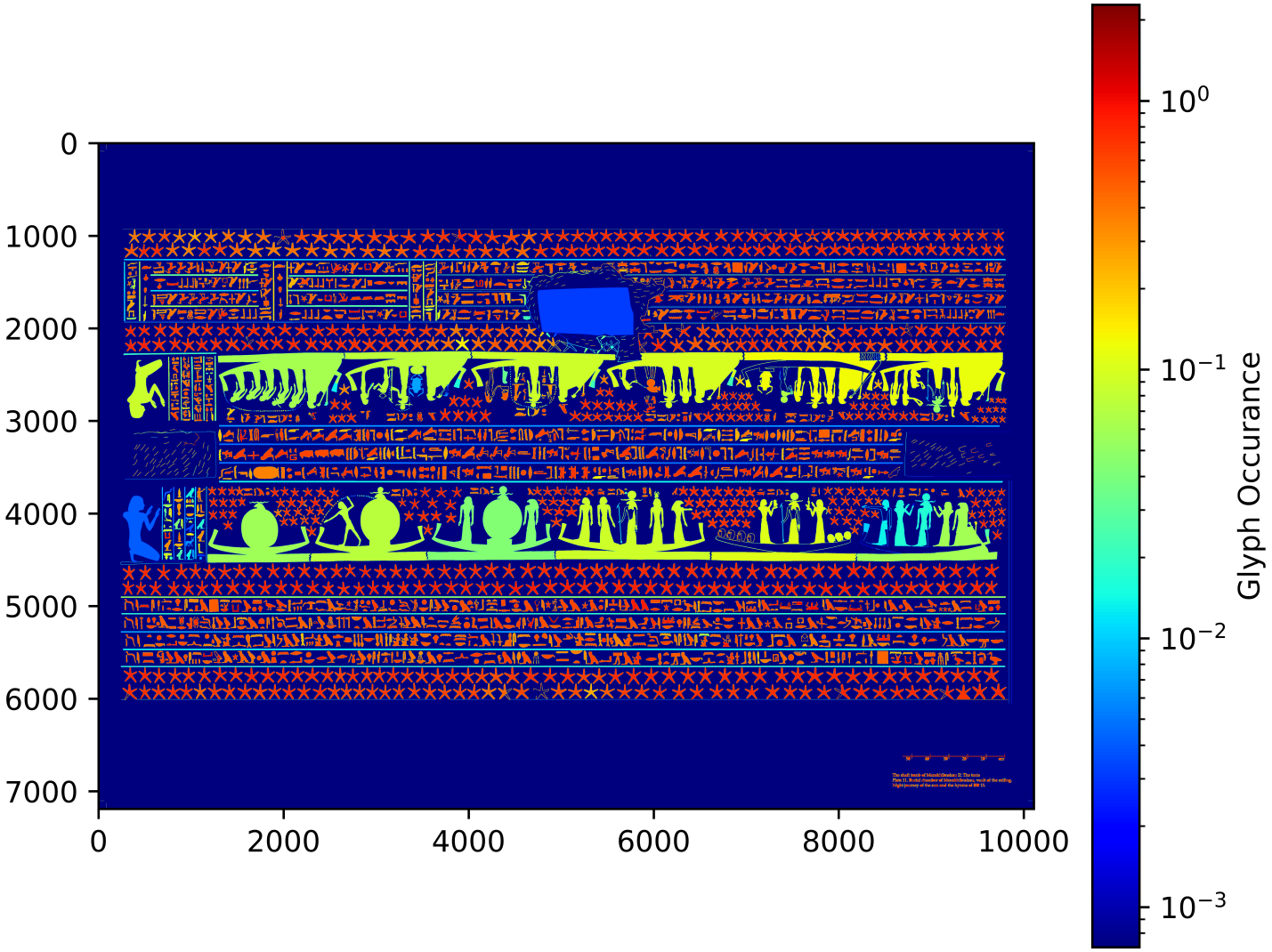


Hieroglyph Detection



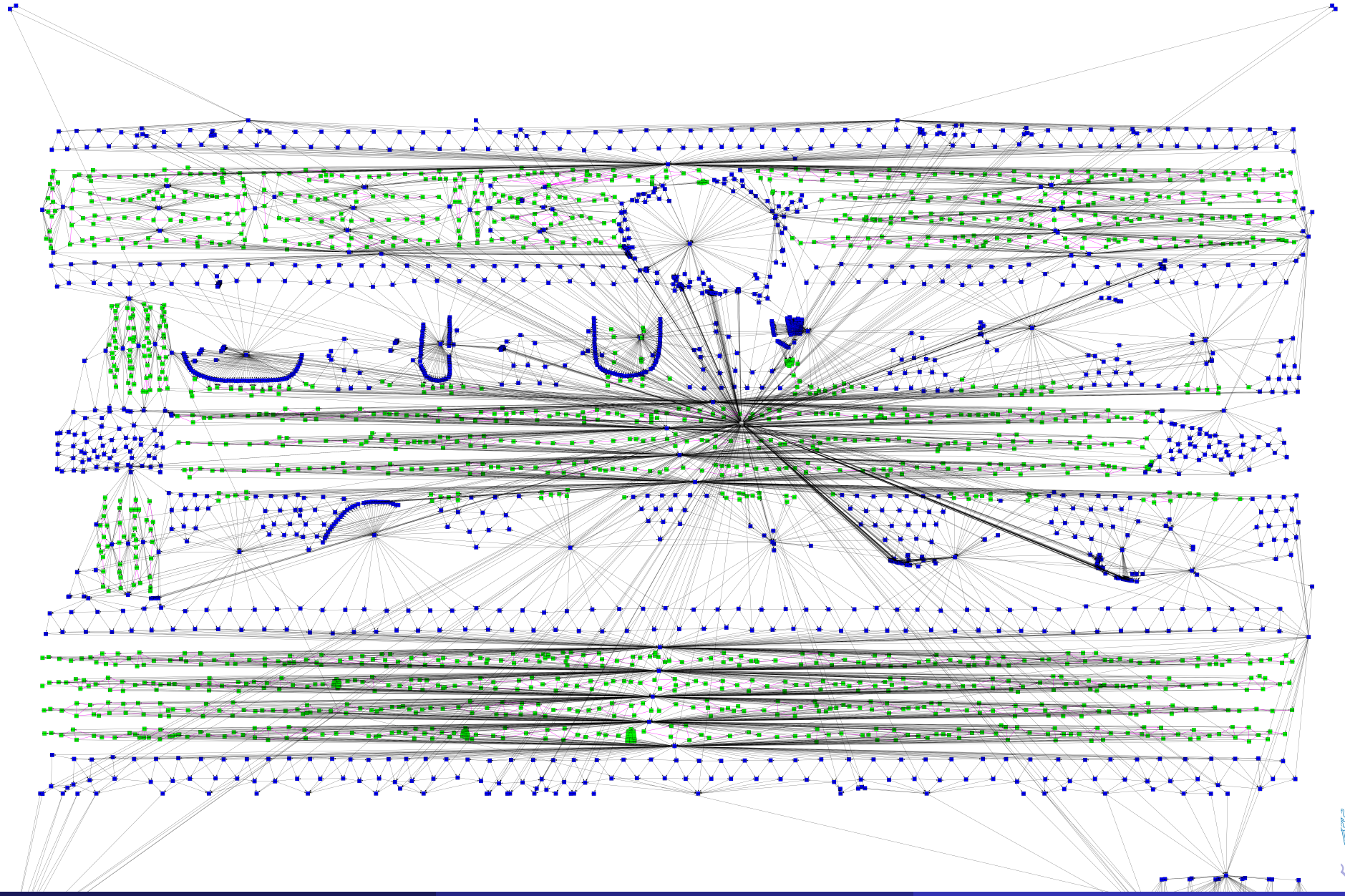
CRAFT detector (no affinities) [BLH+19]

Detection Probability

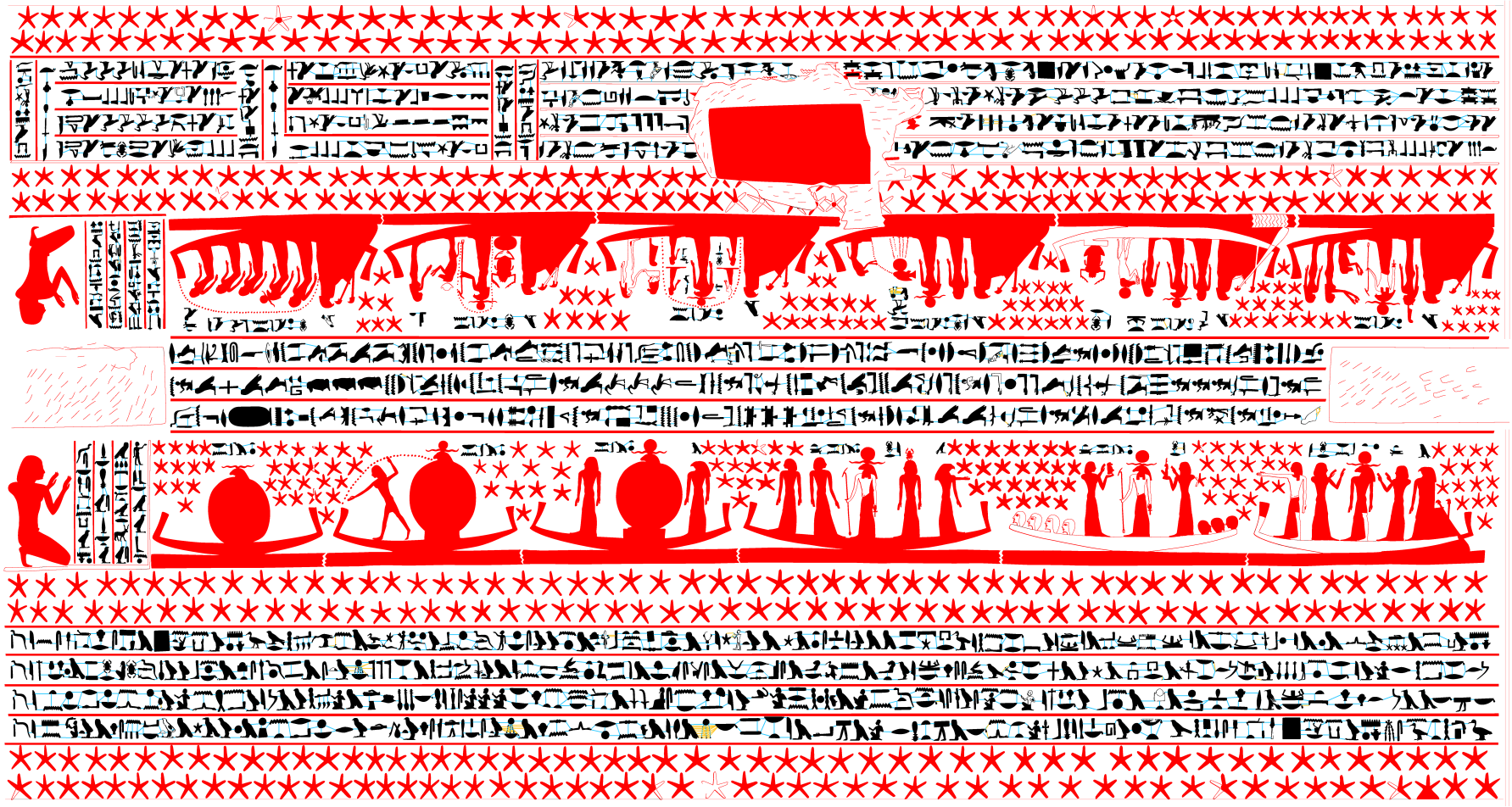


A measure that a blob is a hieroglyph

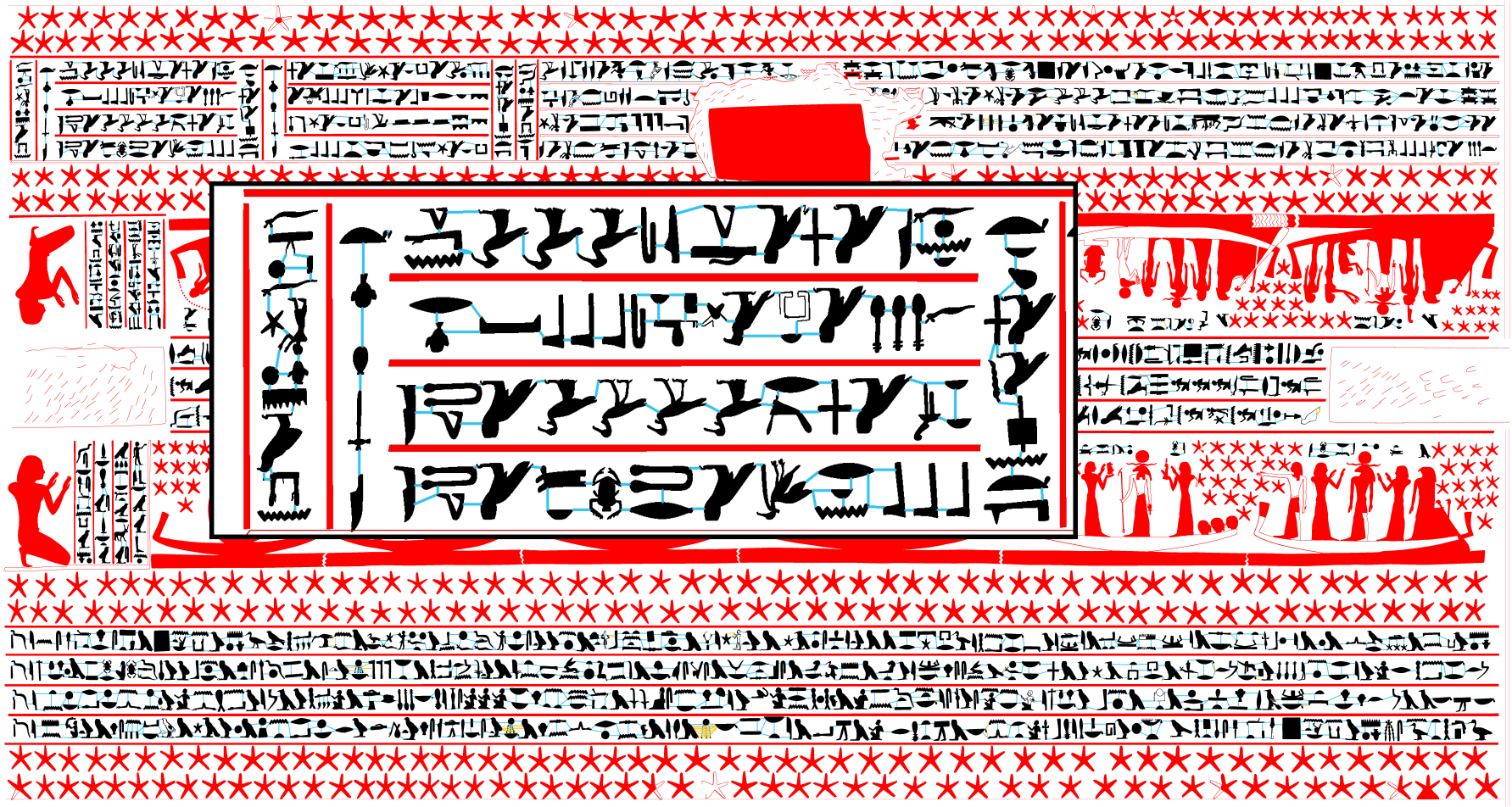
Blob Neighborhood Network



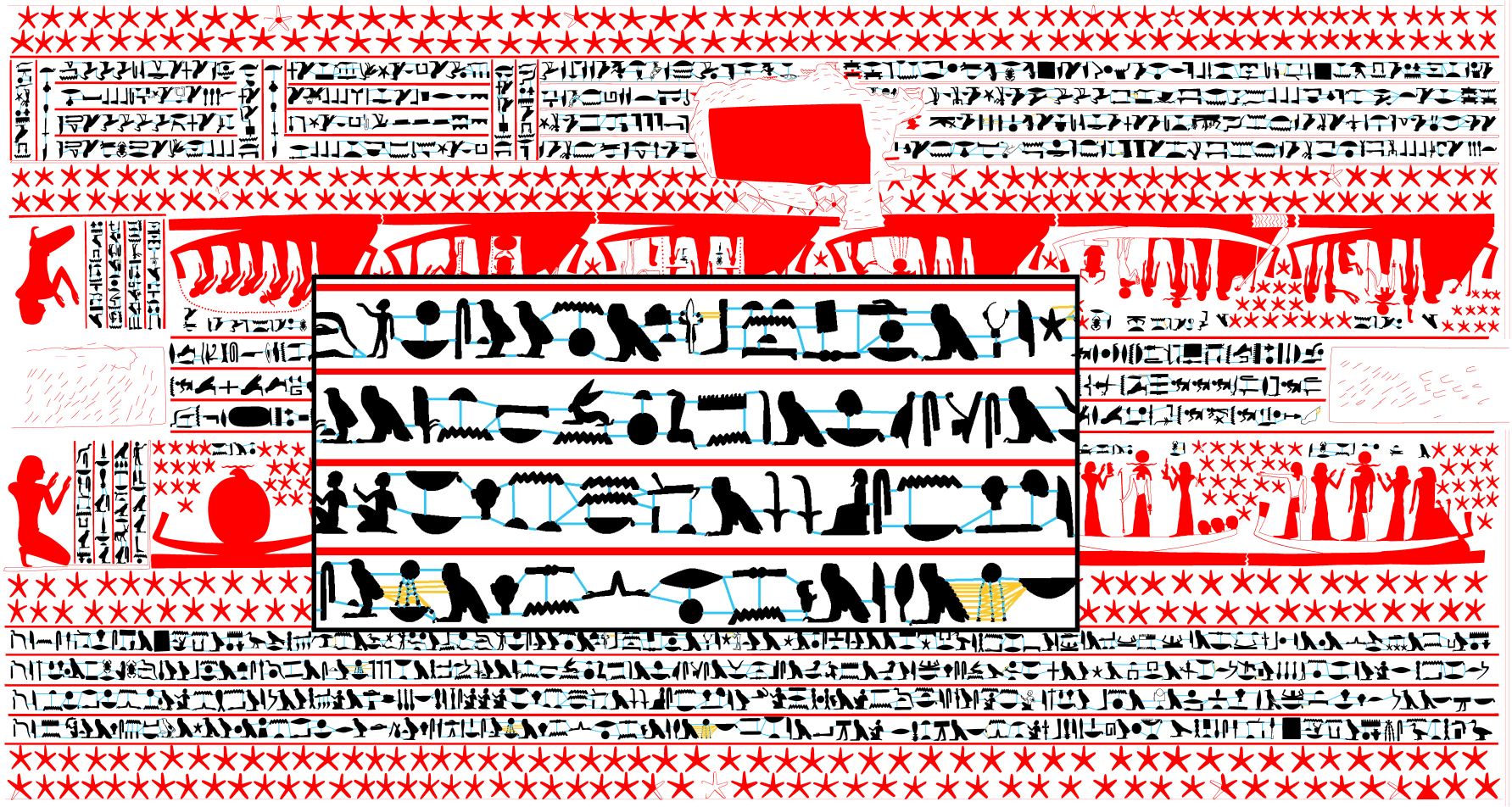
Classified Hieroglyphs, Strips and Neighborhood Edges



Classified Hieroglyphs, Strips and Neighborhood Edges



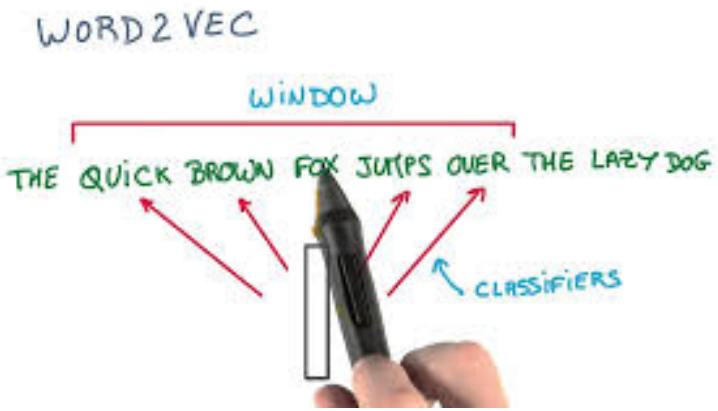
Classified Hieroglyphs, Strips and Neighborhood Edges

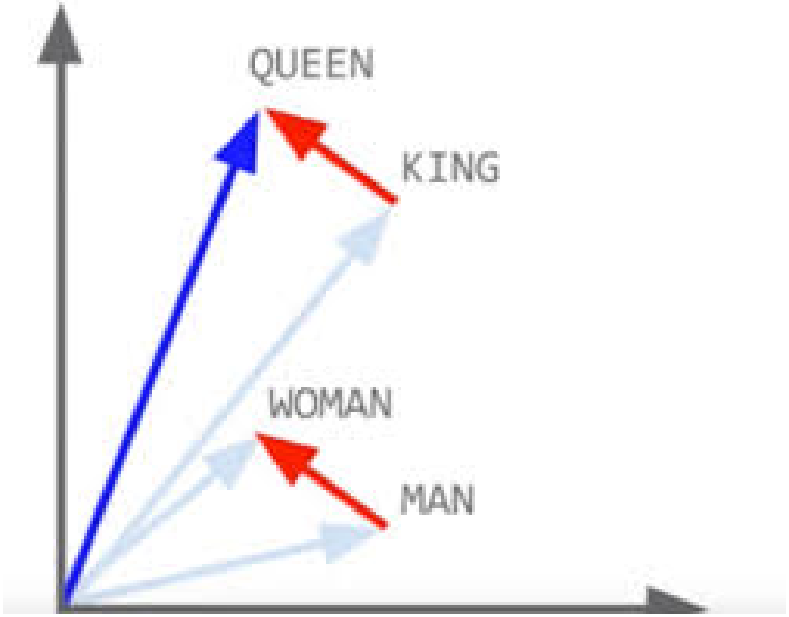


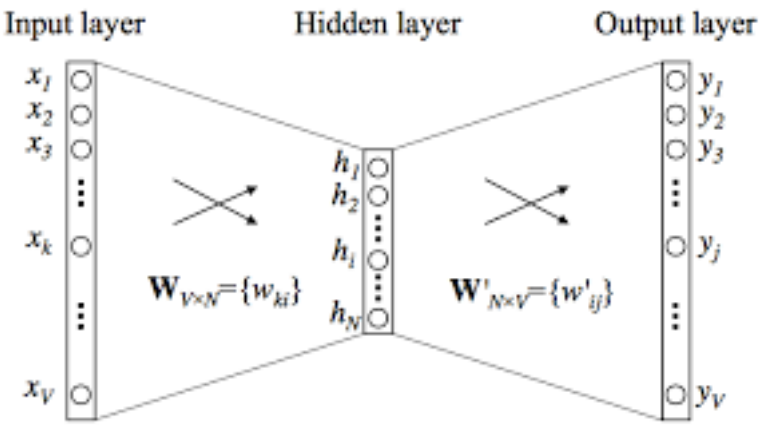
Outline

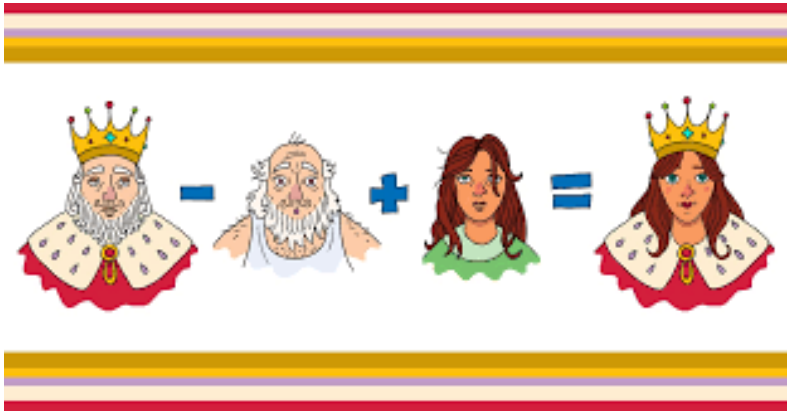
1. Deep Learning
   - Advanced Neural Networks
2. Network Inference
   - Introduction
   - Network Inference Example - Viber
   - Graph Neural Network (GNN)
3. Natural Language Processing (NLP)
   - Embeddings and Neural Network Architectures

Embeddings - Word2vec Word Representation (Skipgram)

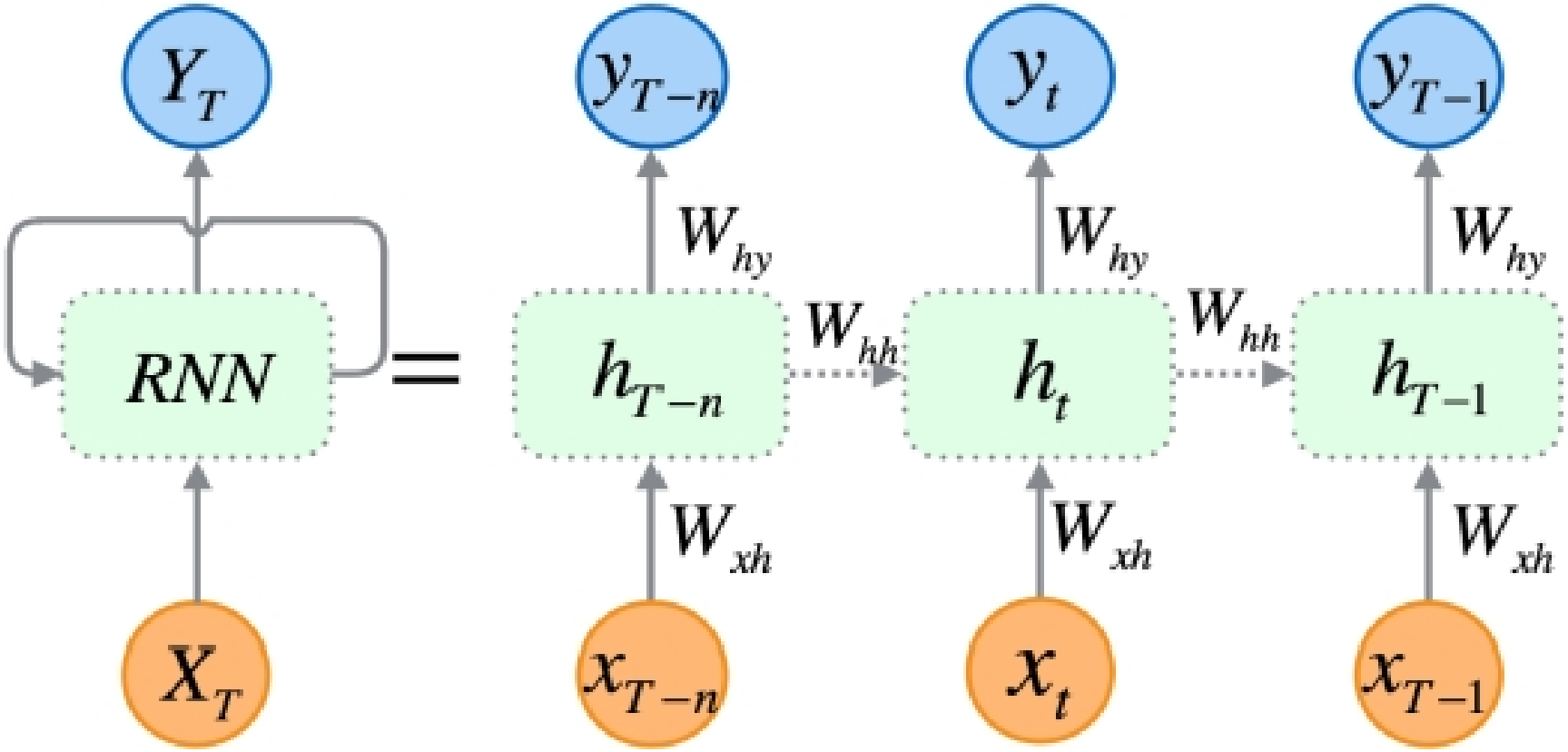








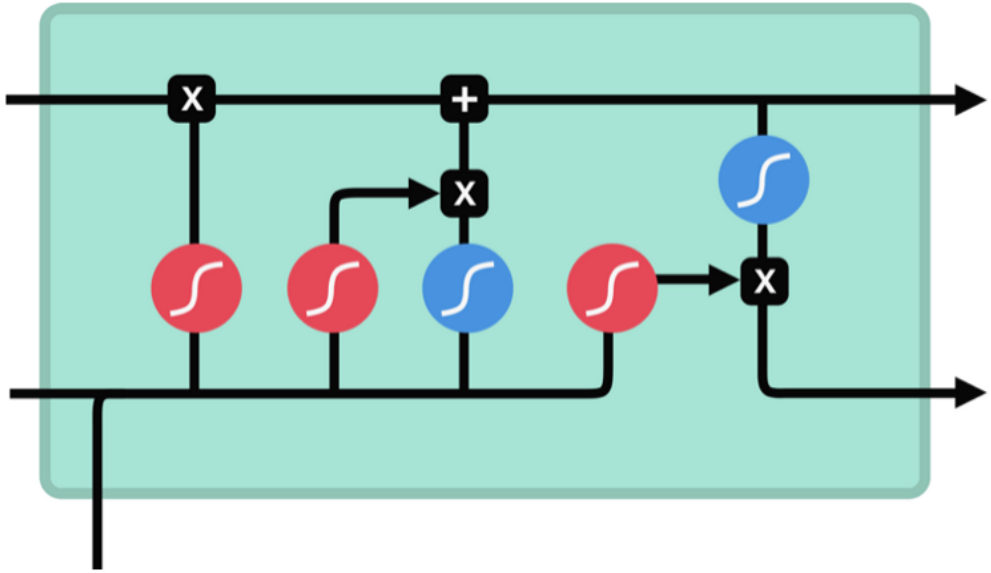
Recurrent Neural Network (RNN)



Used in natural language processing.

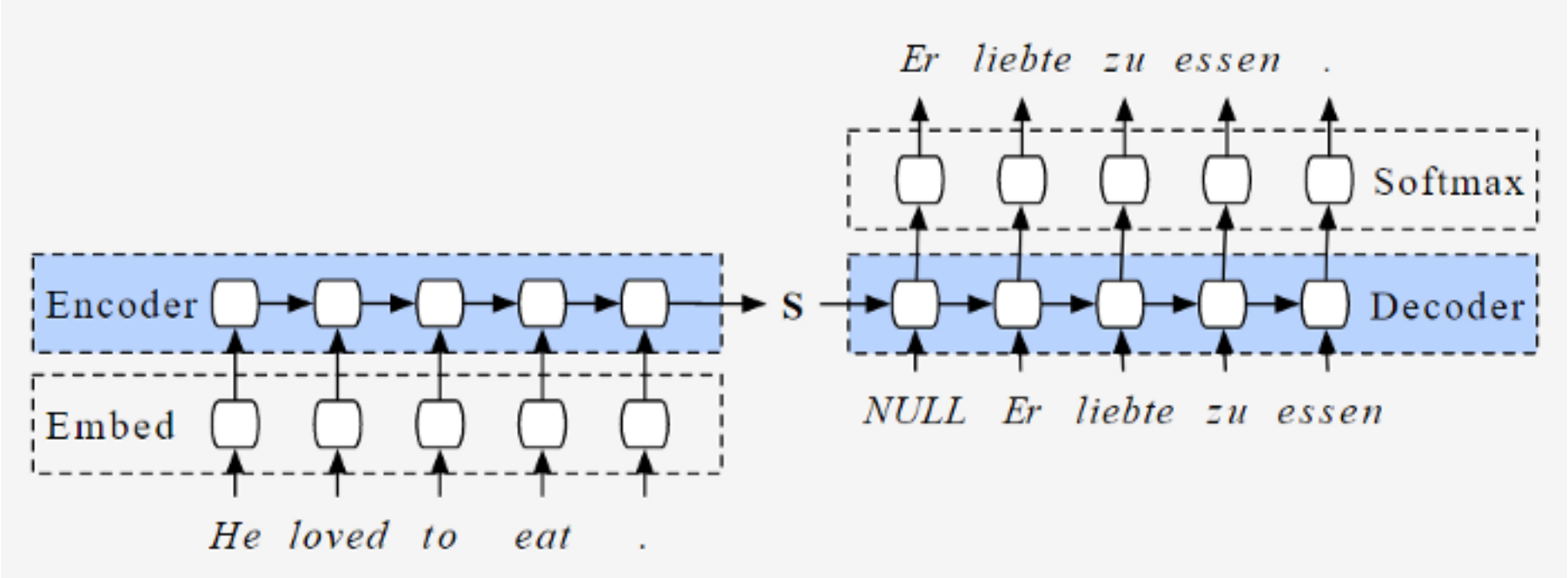
https://www.i2tutorials.com/what-is-the-difference-between-bidirectional-rnn-and-rnn/

Long Short-Term Memory (LSTM) Network [HS97]



Used in natural language processing.

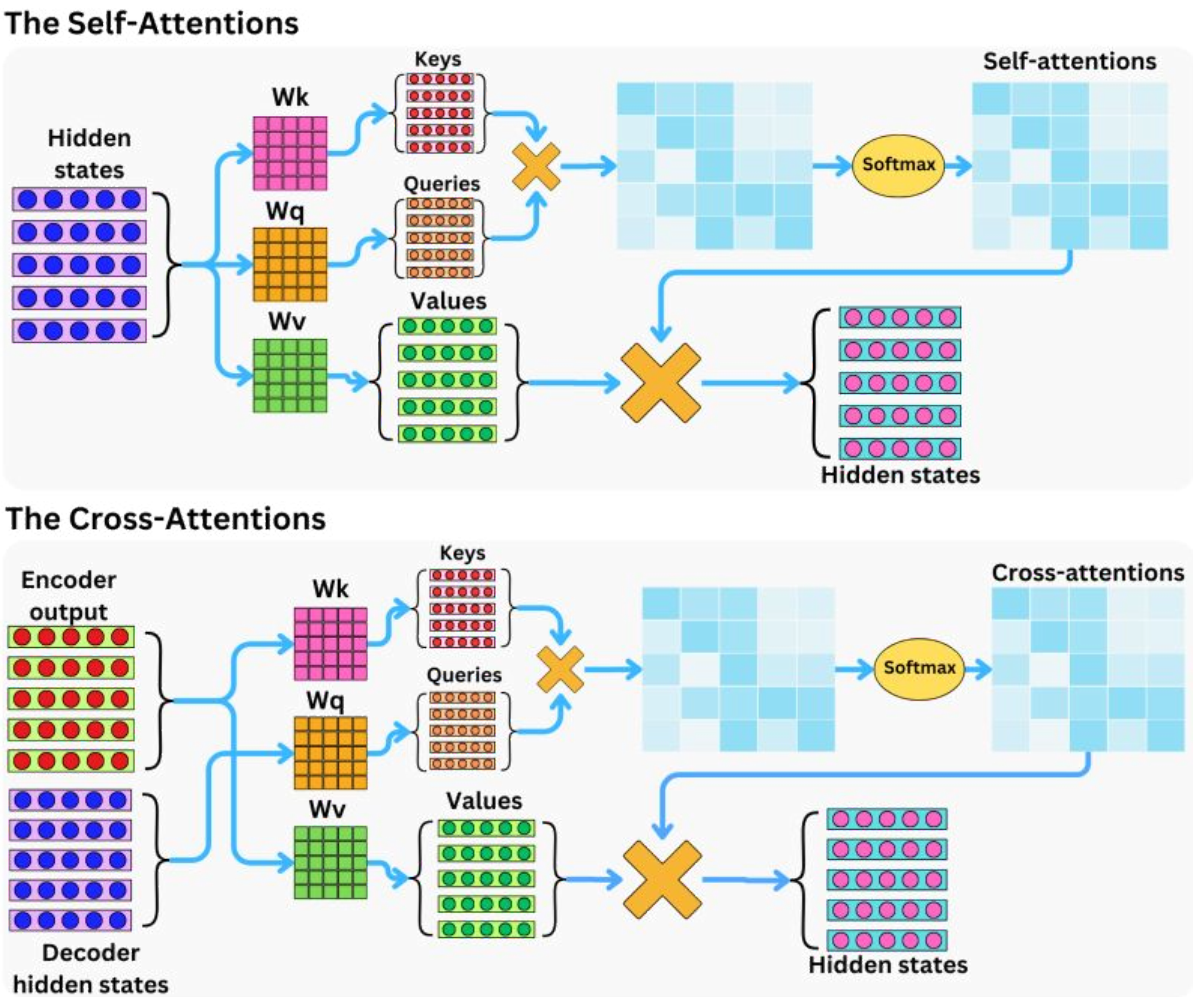
Sequence2Sequence Network [SVL14]



Used in natural language processing.

https://www.analyticsvidhya.com/blog/2020/08/a-simple-introduction-to-sequence-to-sequence-models/

Self and Cross Attention [BCB16]



Used in natural language processing and computer vision.

https://www.linkedin.com/posts/damienbenveniste_

what-is-the-difference-between-self-attention-activity-7211029906166624257-m0Wn/

Transformer Network [VSP+17]

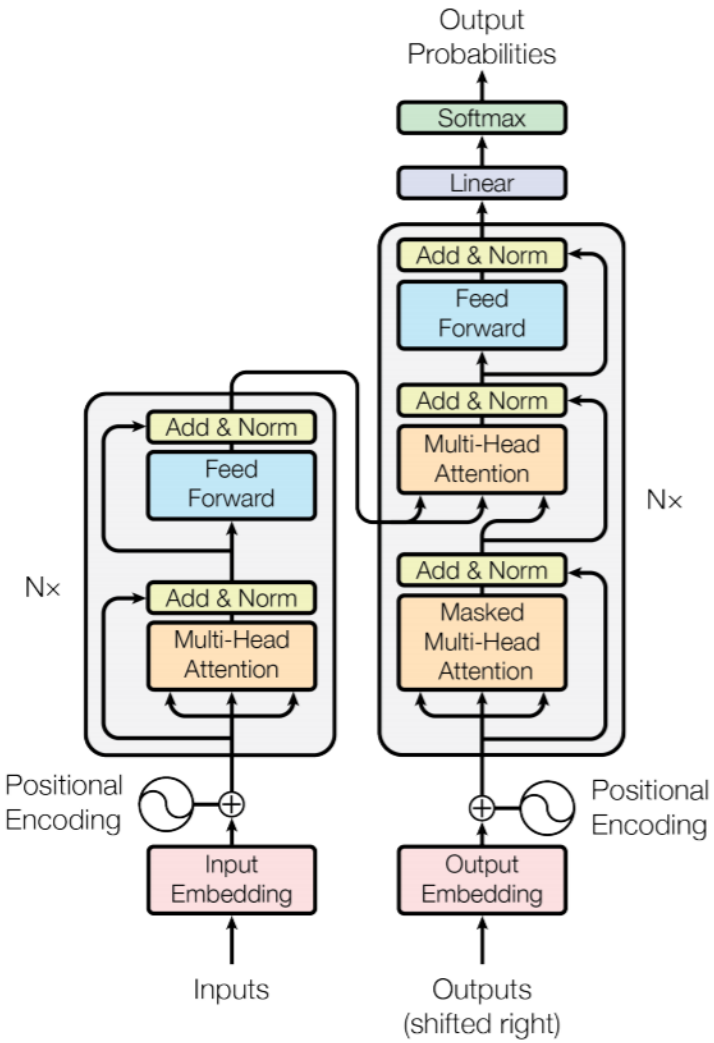


Figure 1: The Transformer - model architecture.

- Used in natural language processing.
- Self-Attention. . . attention applied to a single sequence (position dependencies)
- Multi-head Attention . . . several subspaces of attention
- Language models
  - ELMo . . . March 2018,
  - GPT . . . June 2018, 117Mi pars
  - BERT . . . May 2019, BERTlarge 340M pars,
    - ALBERT(base:12M, xxlarge: 235M), RoBERTa (160GB of text), DistillBERT (66 mil.), DeBERTa (2021.01, 1.5B)
  - GPT2 . . . November 2019, 1.5Bi pars, 8 milion web pages (40GB)
  - XLNet . . . January 2020, Large: 340M pars
  - GPT3 . . . July 2020, 175Bi pars
  - GPT4 . . . March 2023, ≈1.7 trillion pars

https://towardsdatascience.com/transformer-neural-network-step-by-step-breakdown-of-the-beast-b3e096dc857f

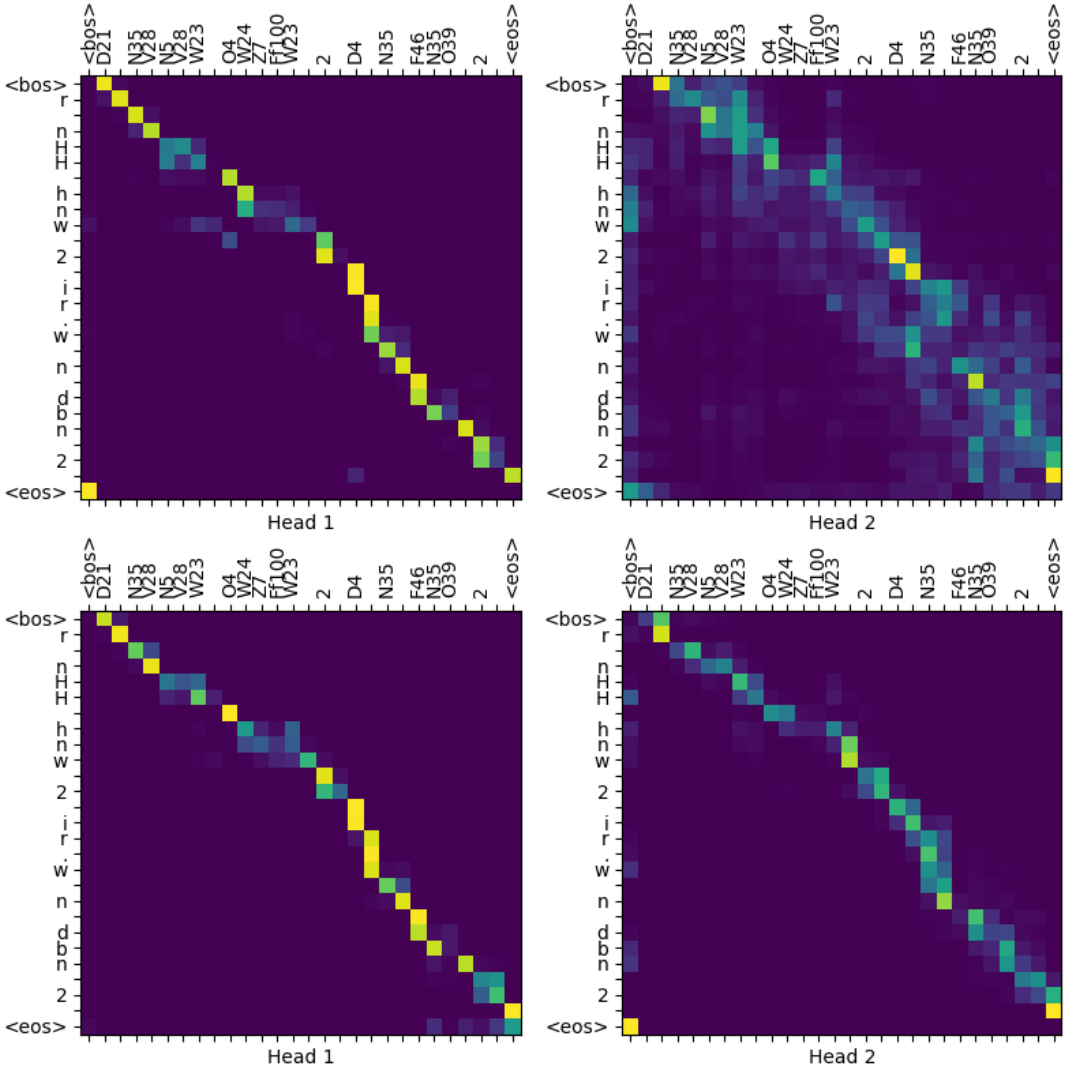
Gardiner Code to Transliteration Translation

ḥtp-dj-nsw ꜣsjr nb ḏdw nṯr ꜥꜣ nb ꜣbḏw

Htp-dj-nsw Asjr nb Ddw nTr aA nb AbDw

An offering which the king gives (to) Osiris, lord of Djedu, great god, lord of Abydos

Model 7 Cross Attention Visualization (2H/1B+2H/2B)



THANK YOU

References I

[BCB16] Dzmitry Bahdanau, Kyunghyun Cho, and Yoshua Bengio. Neural machine translation by jointly learning to align and translate, 2016.

[BLH+19] Youngmin Baek, Bado Lee, Dongyoon Han, Sangdoo Yun, and Hwalsuk Lee. Character region awareness for text detection. In *2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 9357–9366, 2019.

[HS97] Sepp Hochreiter and Jürgen Schmidhuber. Long Short-Term Memory. *Neural Computation*, 9(8):1735–1780, 11 1997.

[Kol09] Eric D. Kolaczyk. *Statistical Analysis of Network Data: Methods and Models*. Springer, 2009.

[MBKK15] Radek Mařík, Pavel Bezpalec, Jan Kučerák, and Lukáš Kencl. Revealing viber communication patterns to assess protocol vulnerability. In *2015 International Conference on Computing and Network Communications (CoCoNet). Leonia, NJ 07605: EDAS Conference Services*, pages 502–510, 2015.

[SVL14] Ilya Sutskever, Oriol Vinyals, and Quoc V. Le. Sequence to sequence learning with neural networks, 2014.

[VSP+17] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N. Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need, 2017.

[ZPIE17] Jun-Yan Zhu, Taesung Park, Phillip Isola, and Alexei A Efros. Unpaired image-to-image translation using cycle-consistent adversarial networkss. In *Computer Vision (ICCV), 2017 IEEE International Conference on*, 2017.