



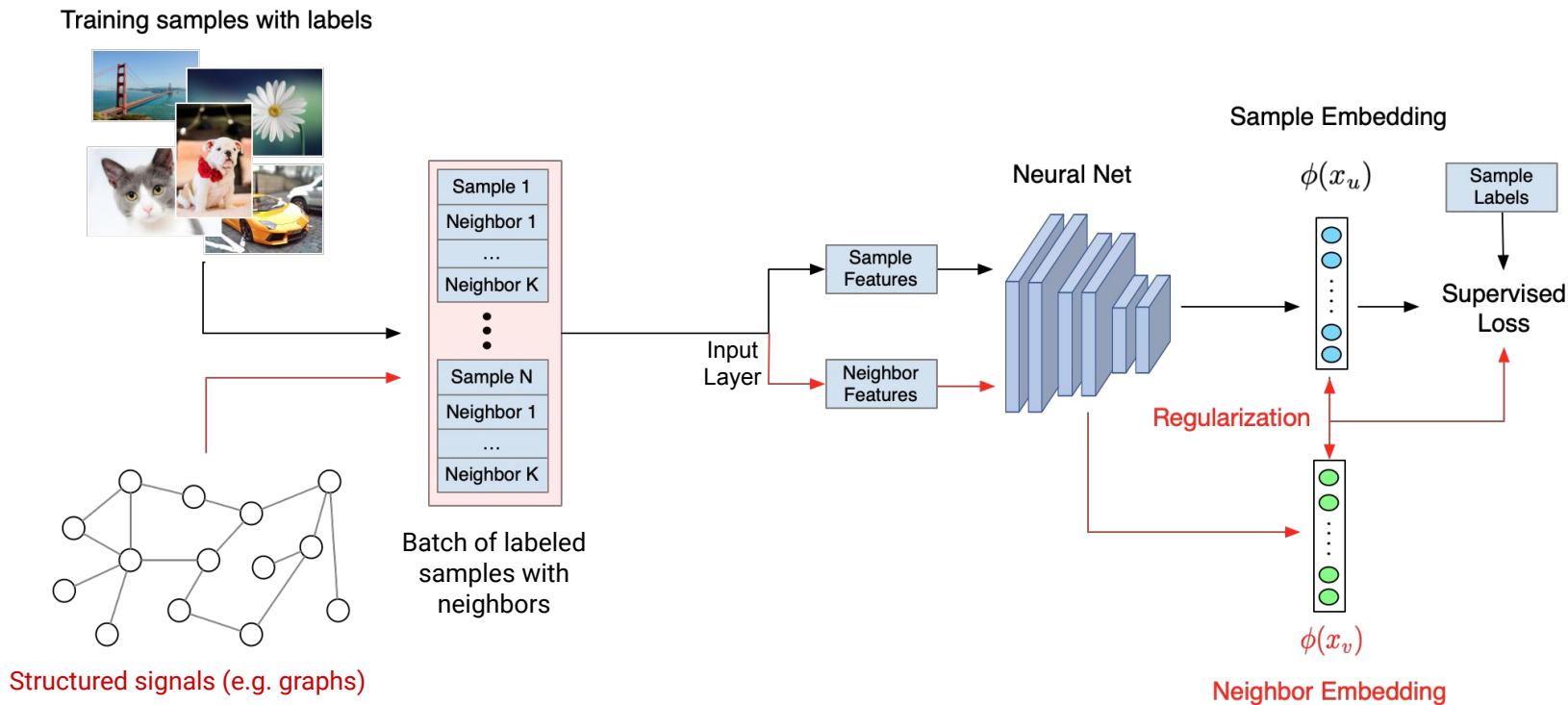
# Data Preprocessing

Allan Heydon



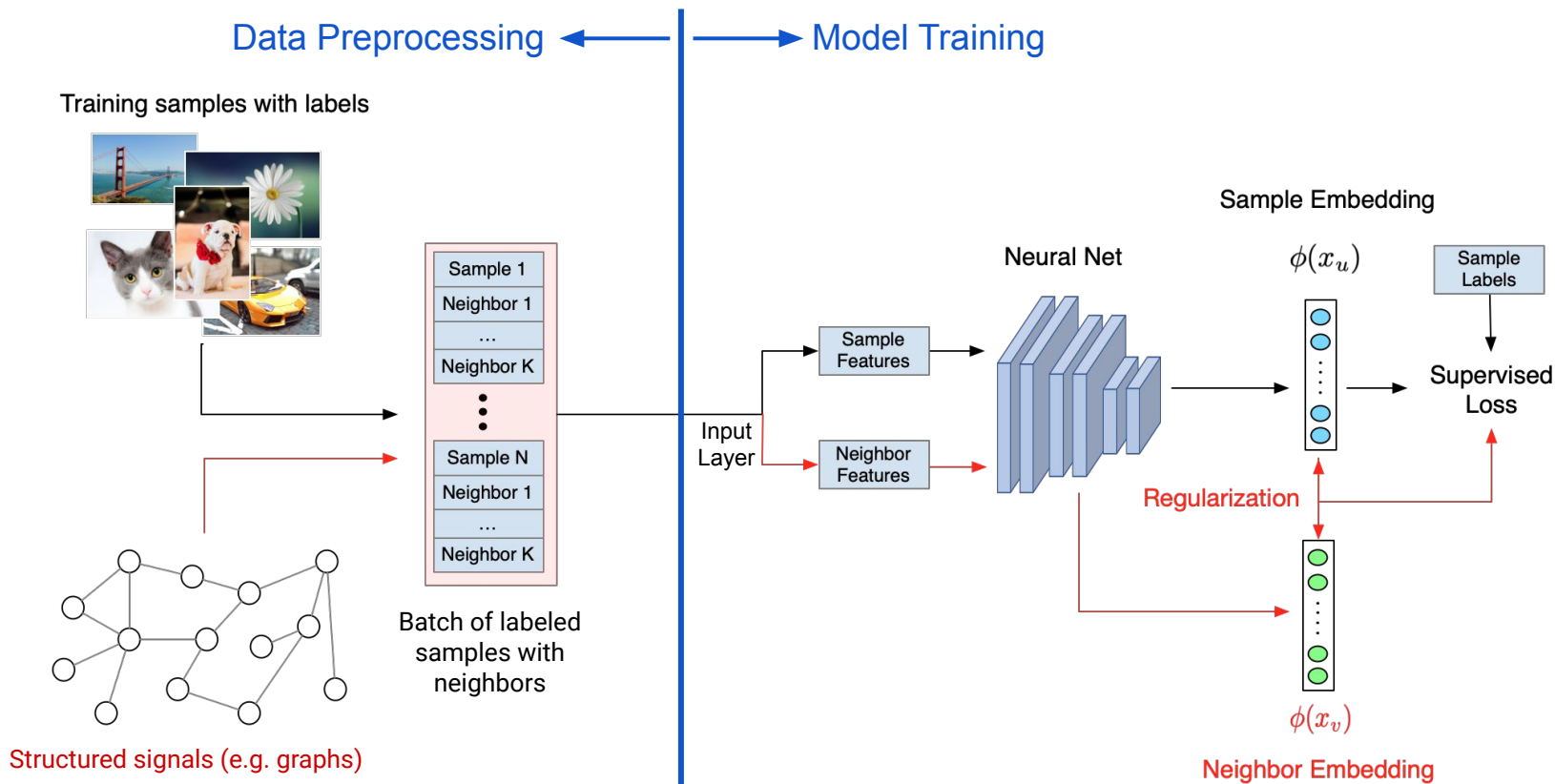


# Data Preprocessing





# Data Preprocessing

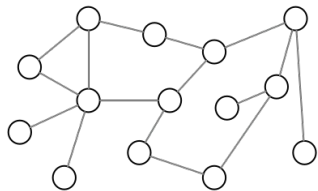




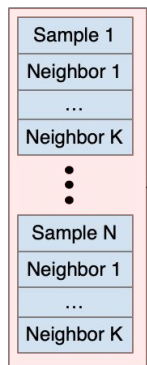
# Data Preprocessing

Data Preprocessing

Training samples with labels



Structured signals (e.g. graphs)



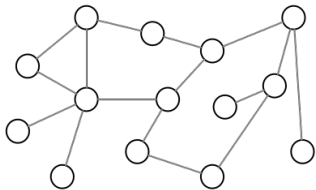
Batch of labeled  
samples with  
neighbors



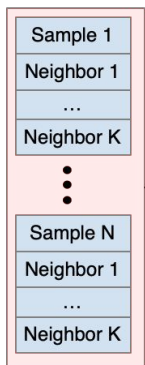
# Data Preprocessing

## Data Preprocessing

### #1 Training samples with labels



Structured signals (e.g. graphs)



Batch of labeled samples with neighbors

1. Training examples
  - Most of these may be unlabeled, but a subset need to be labeled for training.



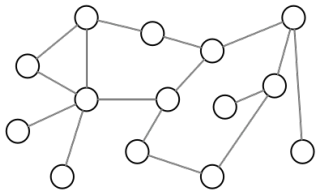
# Data Preprocessing

## Data Preprocessing

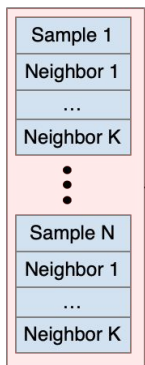
### #1 Training samples with labels



### #2



Structured signals (e.g. graphs)



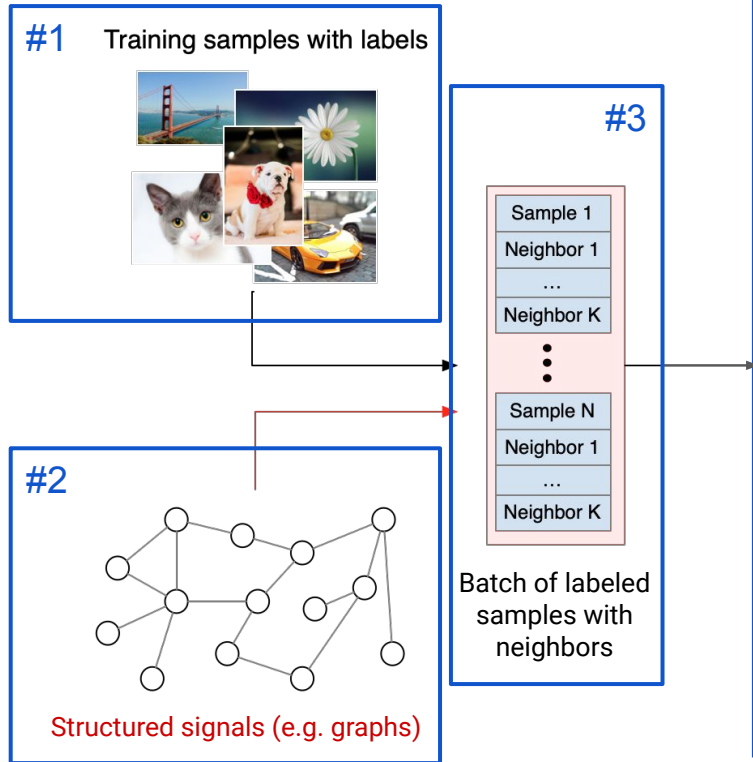
Batch of labeled  
samples with  
neighbors

1. Training examples
  - Most of these may be unlabeled, but a subset need to be labeled for training.
2. Similarity graph
  - Graph nodes denote examples.
  - Weighted graph edges represent degree of similarity between pairs.
  - Two forms:
    - Natural
    - Constructed



# Data Preprocessing

## Data Preprocessing



1. Training examples
  - Most of these may be unlabeled, but a subset need to be labeled for training.
2. Similarity graph
  - Graph nodes denote examples.
  - Weighted graph edges represent degree of similarity between pairs.
  - Two forms:
    - Organic
    - Constructed
3. Combine labeled examples with their neighbors in the similarity graph



# Training Examples

- Represented by `tensorflow.Example` protocol buffers.
- Stored in [TFRecord files](#), which contain a sequence of Examples.
- Each example must define a string-valued feature containing its globally unique ID.
- Labeled examples are distinguished by defining a single-valued feature containing the label value.
- The NSL toolset requires that labeled and unlabeled examples are stored in separate TFRecord files.

## #1 Training samples with labels



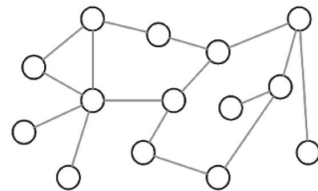




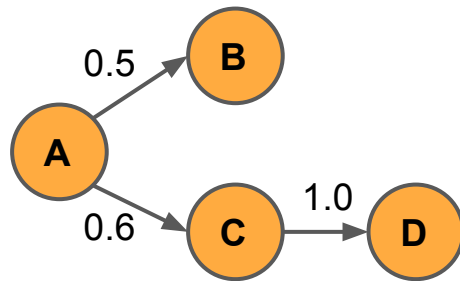
# Similarity Graphs

- Represented using TSV files, each with 3 columns:
  - `source_id <TAB> target_id [ <TAB> edge_weight ]`
- I/O helper functions:
  - [`nsi.tools.read\_tsv\_graph\(filename\)`](#): graph
  - [`nsi.tools.write\_tsv\_graph\(filename, graph\)`](#): None
- Python graph representation:
  - dict: `source_id`  $\rightarrow$  (dict: `target_id`  $\rightarrow$  `edge_weight`)
  - Example: `{ "A": { "B": 0.5, "C": 0.6 }, "C": { "D": 1.0 } }`
- Graph utils:
  - [`nsi.tools.add\_edge\(graph, edge\)`](#): Boolean
  - [`nsi.tools.add\_undirected\_edges\(graph\)`](#): None

#2

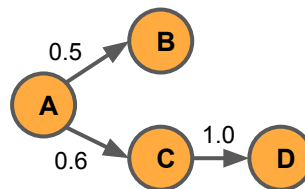
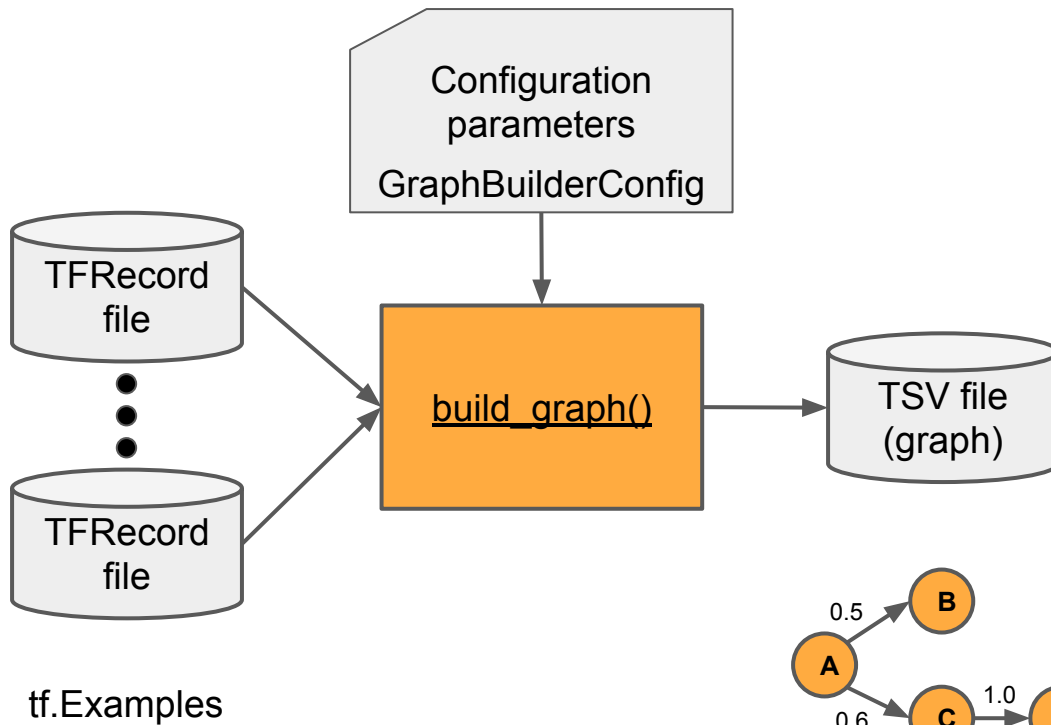


Structured signals (e.g. graphs)

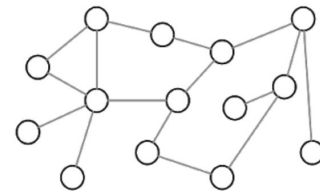




# Graph Building



#2

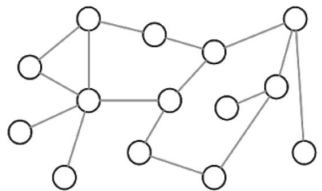


Structured signals (e.g. graphs)



# Graph Building algorithm

#2

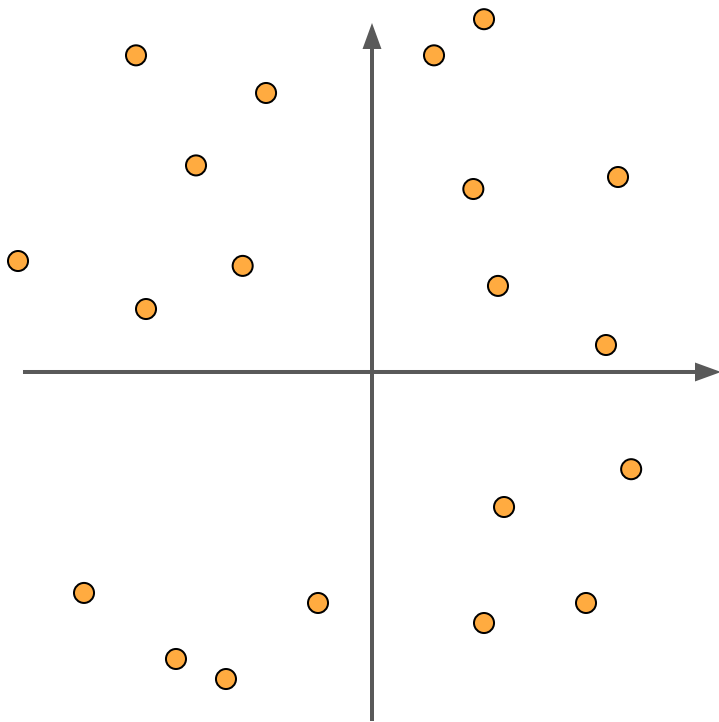


Structured signals (e.g. graphs)

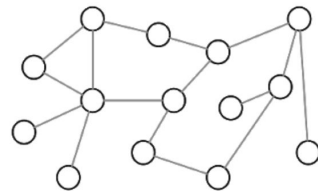
- Requires every input to have 2 features:
  - `id` -- singleton `bytes_list` identifying example
  - `embedding` -- dense `float_list` containing an embedding
- All embeddings must have the same dimension  $d$
- Compares all pairs of inputs for similarity
- Similarity computation:
  - `edge_weight = cosine_similarity(embedding1, embedding2)`
  - This is the cosine of the angle between the two embeddings when each is thought of as a vector in  $\mathbb{R}^d$ .
- Problem: # of pairs is  $O(n^2)$ .



# Locality-Sensitive Hashing (LSH)



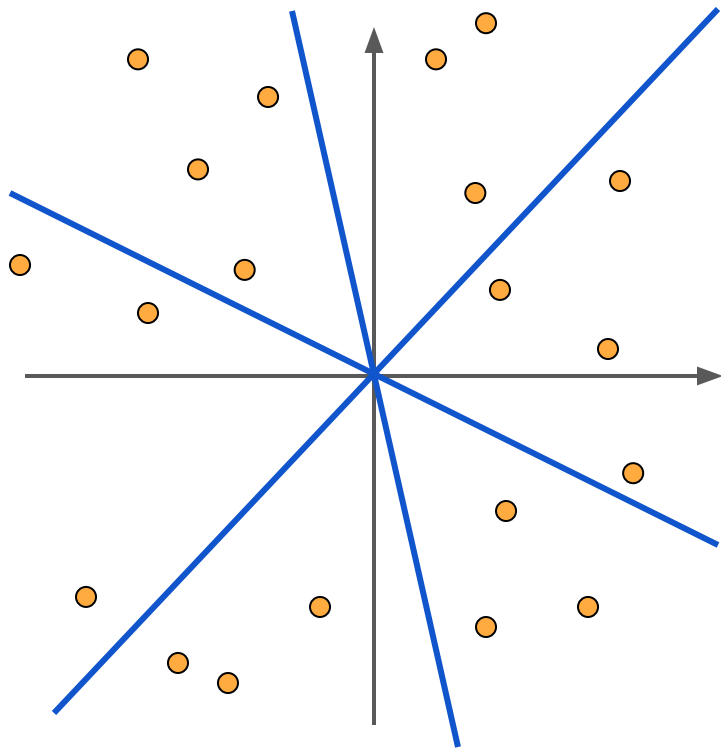
#2



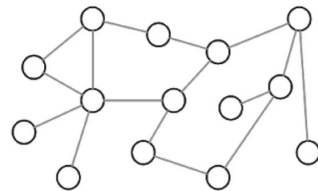
Structured signals (e.g. graphs)



# Locality-Sensitive Hashing (LSH)



#2

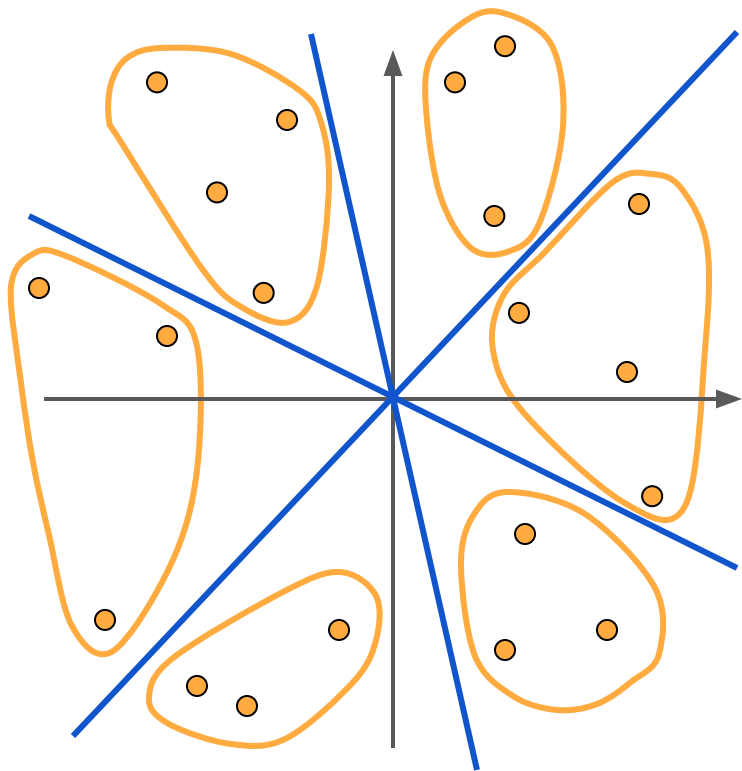


Structured signals (e.g. graphs)

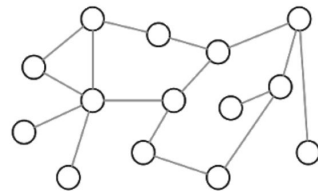
- Randomly split points into *LSH buckets*



# Locality-Sensitive Hashing (LSH)



#2

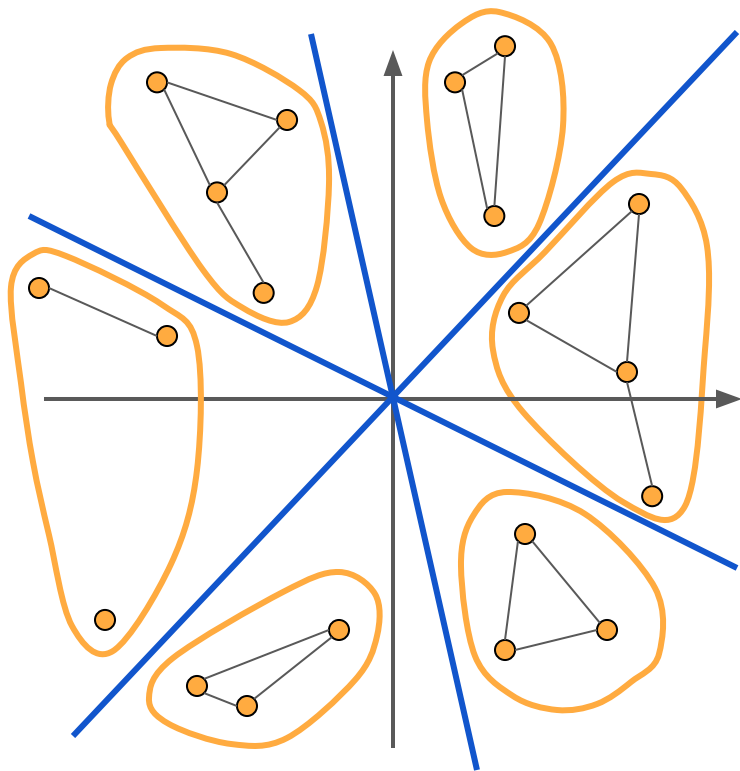


Structured signals (e.g. graphs)

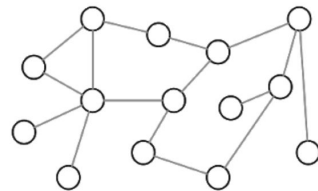
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- Compare all point pairs in each bucket



# Locality-Sensitive Hashing (LSH)



#2

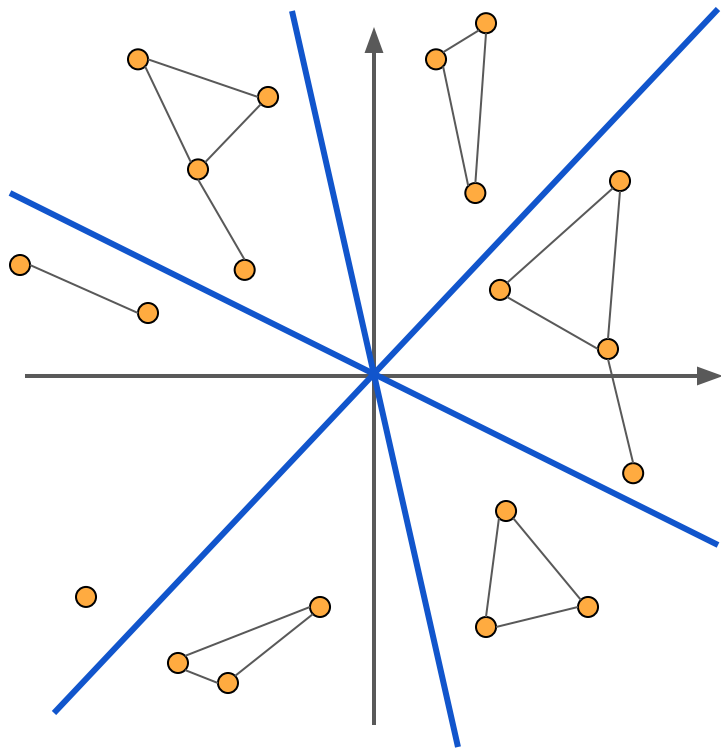


Structured signals (e.g. graphs)

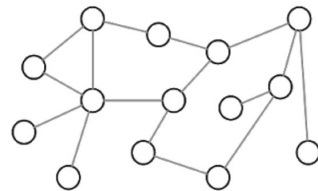
- Randomly split points into *LSH buckets*
- Compare all point pairs in each bucket
- Construct intra-bucket edges



# Locality-Sensitive Hashing (LSH)



#2



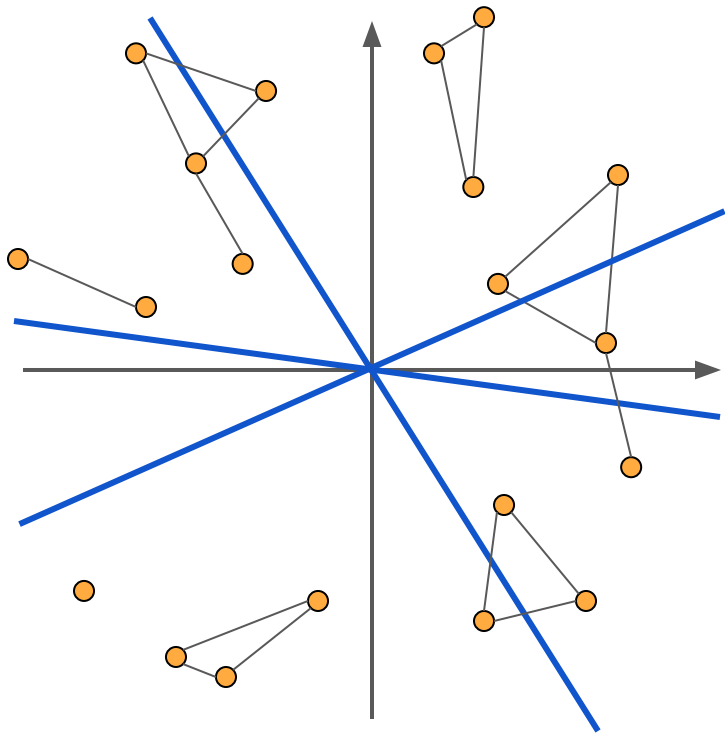
Structured signals (e.g. graphs)

- Randomly split points into *LSH buckets*
- Compare all point pairs in each bucket
- Construct intra-bucket edges
- Note: No edges across buckets!

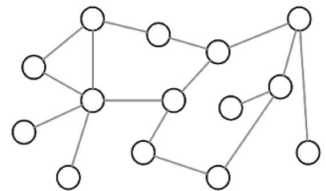




# Locality-Sensitive Hashing (LSH)



#2

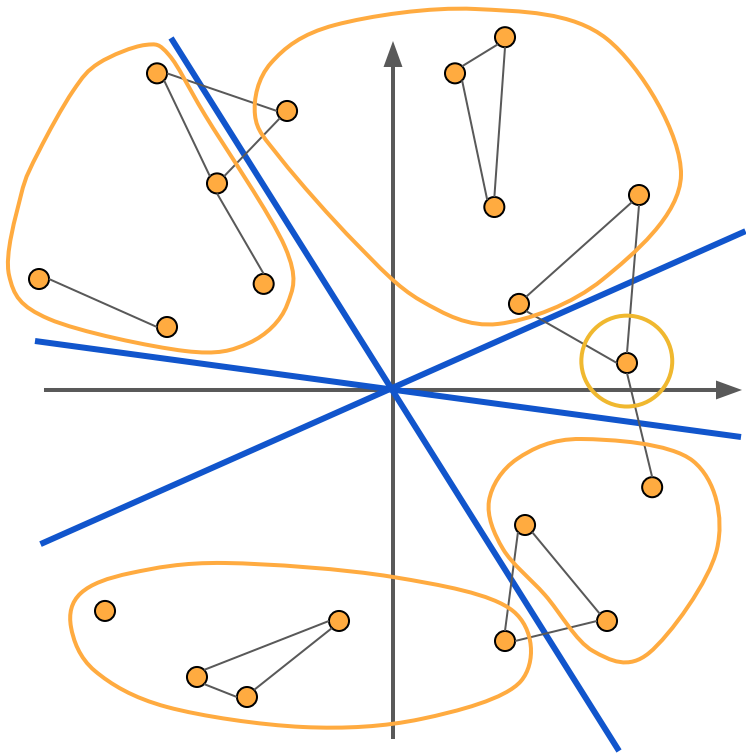


Structured signals (e.g. graphs)

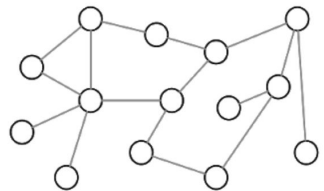
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- Repeat this process multiple times



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#2

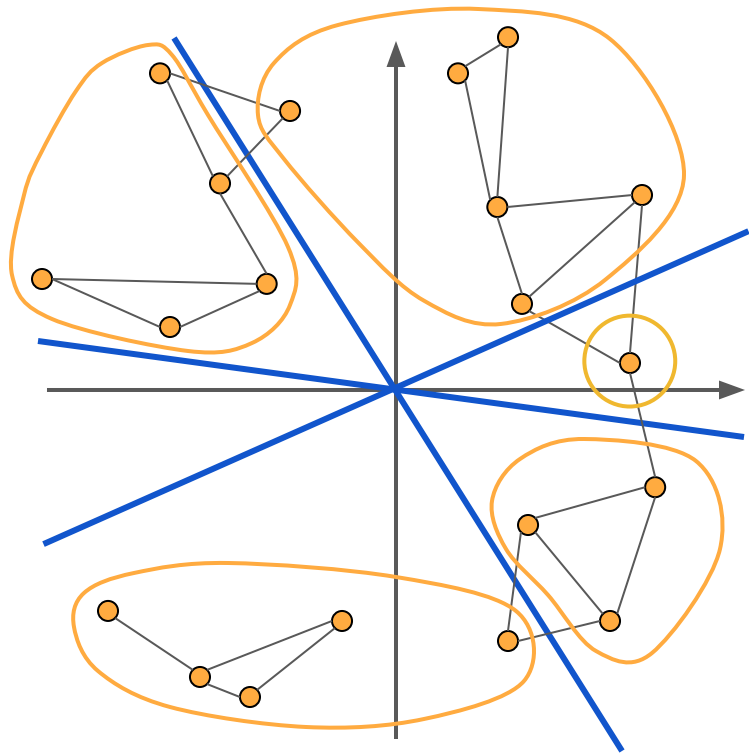


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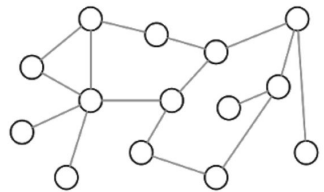
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#2



Structured signals (e.g. graphs)

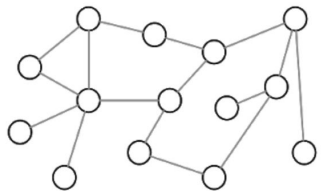
- Randomly split points into *LSH buckets*
- Compare all point pairs in each bucket
- Construct intra-bucket edges
- Note: No edges across buckets!
- Repeat this process multiple times
  - Each *round* of randomized LSH bucketing finds new edges



# nsf.configs.GraphBuilderConfig

- `id_feature_name`: string
  - Name of the feature containing the example ID
- `embedding_feature_name`: string
  - Name of the feature containing the (dense) embedding
- `similarity_threshold`: float
  - Lower bound on cosine similarity for edge to be created
- `lsh_rounds`: int
  - Number of LSH bucketing rounds performed
- `lsh_splits`: int
  - Number of random partitions on each LSH round
  - $\Rightarrow$  Maximum of  $2^{\text{lsh\_splits}}$  LSH buckets per round
- `random_seed`: int

#2

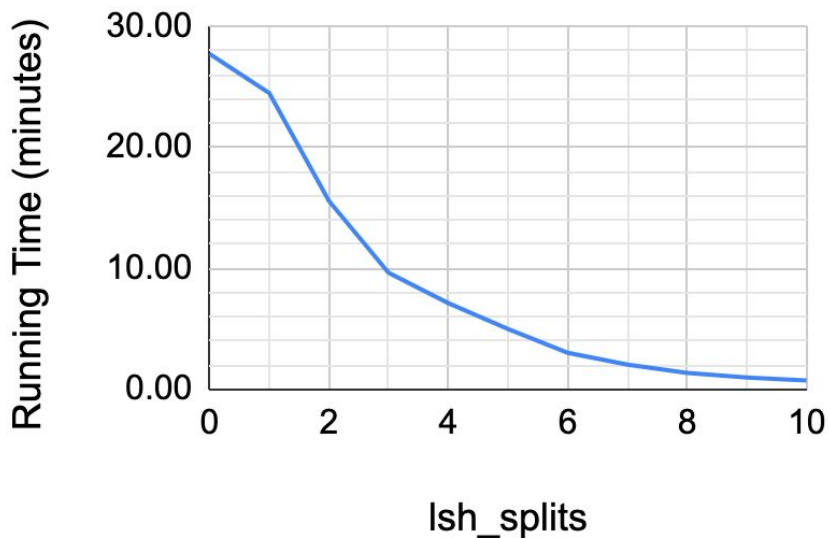


Structured signals (e.g. graphs)

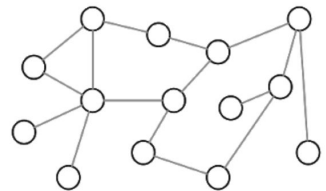


# LSH Splits vs. Rounds

- 50K samples
- 100-D embedding vectors
- 0.9 similarity threshold
- Goal: Achieve 99.7+% recall of all edges resulting from `lsh_splits = 0`.



#2



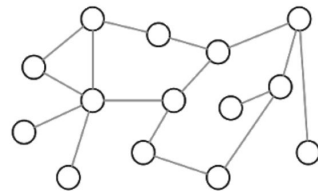
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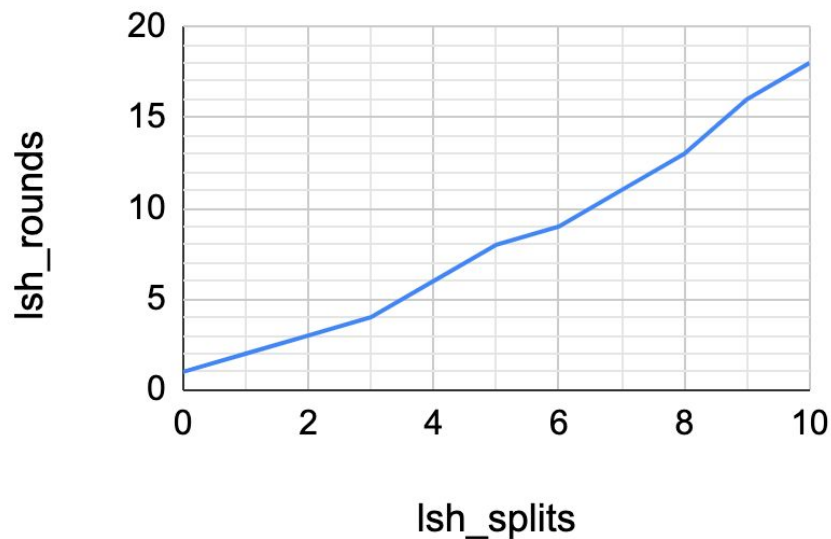
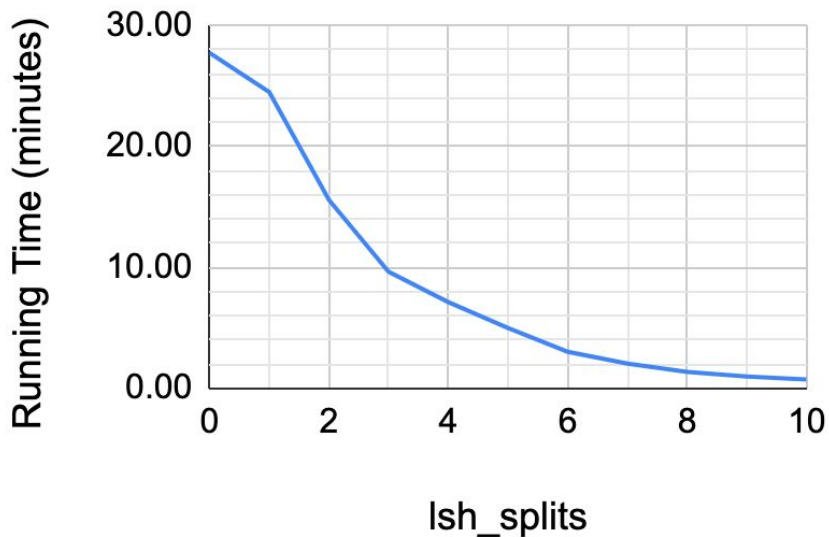
# LSH Splits vs. Rounds

- 50K vertices
- 100-D embedding vectors
- 0.9 similarity threshold
- Goal: Achieve 99.7+% recall of all edges resulting from  $\text{ls\_splits} = 0$ .

#2

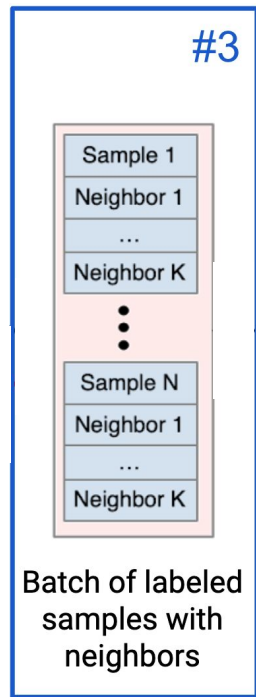
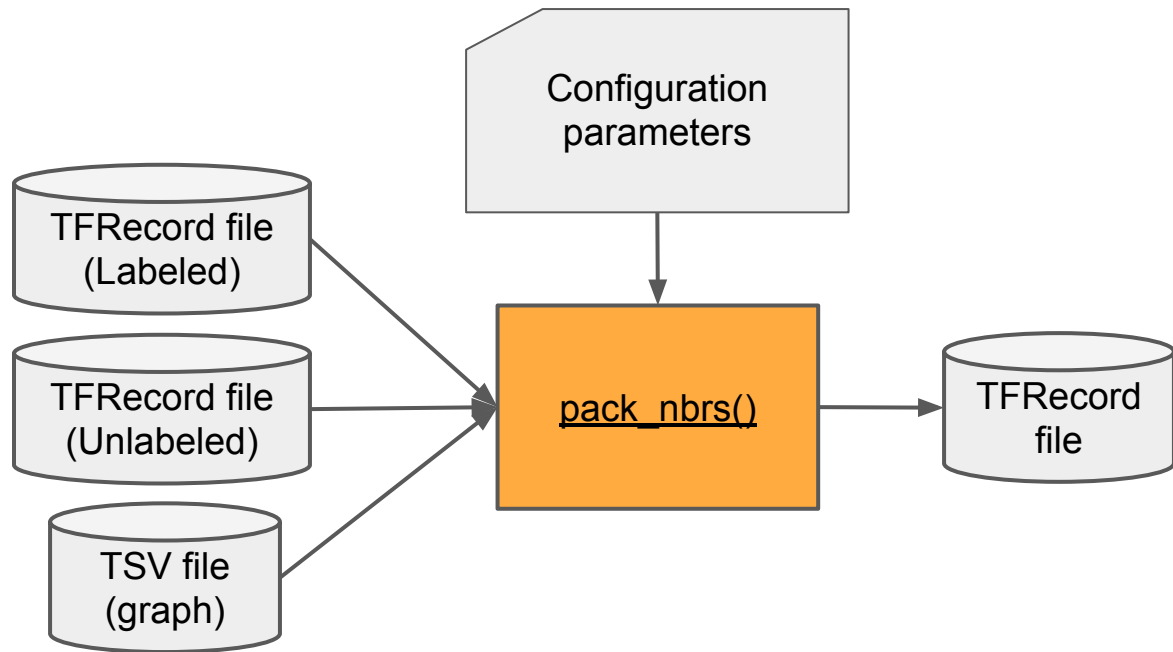


Structured signals (e.g. graphs)





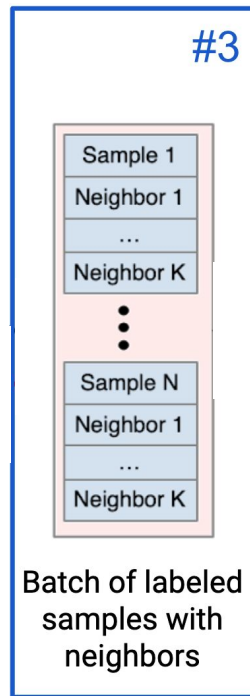
# Packing Neighbors together





## nsi.tools.pack\_nbrs()

- labeled\_examples\_path: string
  - Pathname of TFRecord file containing labeled Examples
- unlabeled\_example\_path: string
  - Pathname of TFRecord file containing unlabeled Examples
- graph\_path: string
  - Pathname of TSV file containing graph edges
- output\_training\_data\_path: string
  - Pathname of TFRecord file where merged training Examples are written
- add\_undirected\_edges: boolean (default=False)
  - If True, all input graph edges are made symmetric
- max\_nbrs: int (default=None)
  - Max # of neighbors to pack with each labeled Example
- id\_feature\_name: string (default="id")
  - Name of the feature containing the example ID







# Running tools as binaries

Both data preprocessing tools can be run as binaries.

Graph Builder:

```
$ python -m neural_structured_learning.tools.build_graph \
  [flags] embedding_file.tfr... output_graph.tsv
```

Pack Neighbors:

```
$ python -m neural_structured_learning.tools.pack_nbrs \
  [flags] labeled.tfr unlabeled.tfr graph.tsv output.tfr
```