Mapping

```
mapping( base: List[string], target: List[string] ) -> List[str]:
2.
      // assuming len(base) == n, len(target) == m
3.
      // there are ((n choose 2) * (m choose 2) * 2) pairs
4.
5.
      possible_pairs = get_all_possible_pairs(base, target)
6.
7.
      // here we going to store the entities that already mapped.
      // the value in index i in both lists will be the map between them.
8.
      // it is clear that both must be in the same length.
10.
     base_already_map, target_already_map = [], []
11.
      while len(base_already_map) < min(len(base), len(target)):</pre>
12.
13.
       // updating the possible pairs according to the entities that already mapped
        // the idea is to not break the entities that already mapped.
14.
15.
        update_possible_pairs(possible_pairs, base_already_map, target_already_map)
16.
        // we want the pair with the best score.
17.
18.
        // the meaning of pair is for example: earth→electrons AND sun→nucleus.
19.
        res = get_best_pair_mapping(possible_pairs)
20.
        if res["score"] > 0:
21.
          // updating the already mapped lists.
22.
          // res["base"][0] \rightarrow res["target"][0], res["base"][1] \rightarrow res["target"][1]
23.
24.
          update_list(base_already_map, res["base"])
25.
          update_list(target_already_map, res["target"])
26.
        else:
27.
          // no map found at all.
28.
          break
29.
     return [f''\{b\} \rightarrow \{t\}'' \text{ for b, t in } zip(base_already_map, target_already_map)]
30.
```

Clustering + score

```
1. get_score(e_1: tuple, e_2: tuple):
2.
3.
      score = 0
4.
      // we count both directions, for example for mapping earth→electrons, sun→nucleus
5.
      // we will count (earth:sun,electrons:nucleus) and (sun:earth,nucleus:electrons)
6.
      for i in range(2): // direction
7.
        // e_1 and e_2 will flip in the second iteration (direction..)
8.
        props_1 = get\_edge\_props(e_1) // List[str]
9.
         props_2 = get\_edge\_props(e_2) // List[str]
10.
11.
         // this will create a full bipartite graph between props<sub>1</sub> and props<sub>2</sub>
12.
         similarity_edges = get_edges_weights(props<sub>1</sub>, props<sub>2</sub>) // List[Tuple[str, str, float]]
13.
14.
         // clustering is using AgglomerativeClustering of sklearn.cluster
15.
         // \ \underline{\text{https://scikit-learn.org/stable/modules/generated/sklearn.cluster.AgglomerativeClustering.html}
16.
         // distance_threshold → how close the props in the cluster
         clusters_props<sub>1</sub> = clustering(props<sub>1</sub>, distance_threshold) // Dict[int, List[str]]
17.
18.
         clusters_props2 = clustering(props2, distance_threshold) // Dict[int, List[str]]
19.
         // between every two clusters (from the opposite side of the bipartite) we will take
20.
         // only one edge, which will be the one with the maximum weight.
21.
22.
         clusters_edges = get_clusters_edges( similarity_edges, clusters_props<sub>1</sub> , clusters_props<sub>1</sub> )
23.
24.
        // we want the maximum-weight of full bipartite matching
        // we will use networkx algorithm of minimum_weight_full_matching
25.
26.
         // https://networkx.org/documentation/stable/reference/algorithms/generated/networkx.algorithms.bipartite.matching.minimum_weight_full_matching.html
27.
         best_matching = maximum_weight_full_matching( clusters_edges )
28.
         score += sum([edge[2] for edge in best_matching])
29.
30.
      return score
```

```
1. get_edges_weights( props_edge_1: List[string], props_edge_2: List[string] ):
2.
3.
      edges = []
4.
      for p_1 in props\_edge\_1:
        for p_2 in props\_edge\_2:
5.
          // similarity is calculated by cosine-similarity.
6.
          // https://pytorch.org/docs/stable/generated/torch.nn.CosineSimilarity.html
7.
          edges. append (p_1, p_2, similarity(p_1, p_2))
8.
9.
10.
      return edges
```