Large-scale Discriminative n-gram Language Models for Statistical Machine Translation

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Language Model: Data Mismatch

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  - But, the LM will be used to rank MT outputs
  - MT outputs differ substantially from Gigaword
- **Can we make the LM task-specific without losing its big advantage in using enormous monolingual data?**

Task: reranking MT outputs

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- **Decision rule**

$$e^* = \arg\max_{e \in \mathrm{TRANS}(f)} s(f,e)$$

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- Features

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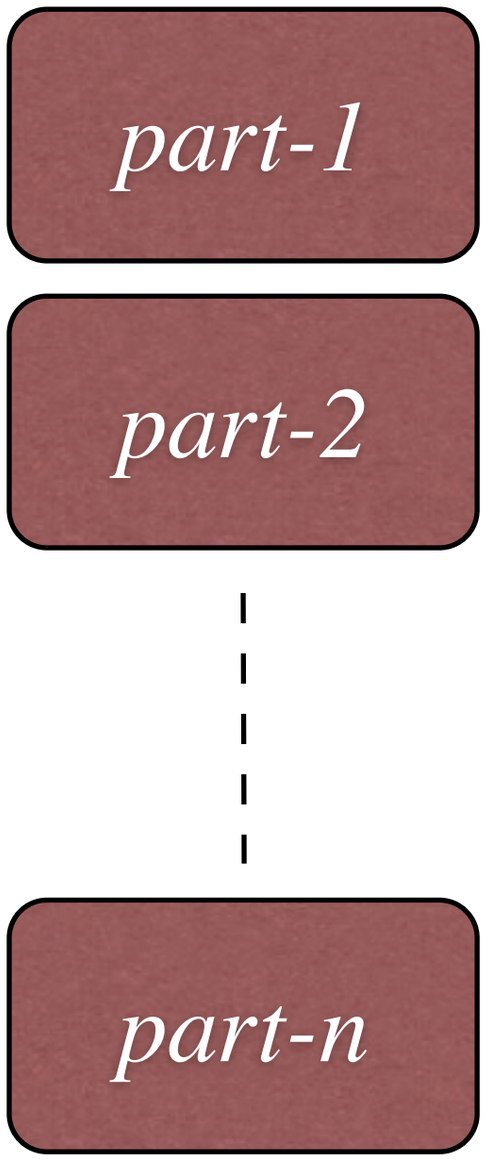

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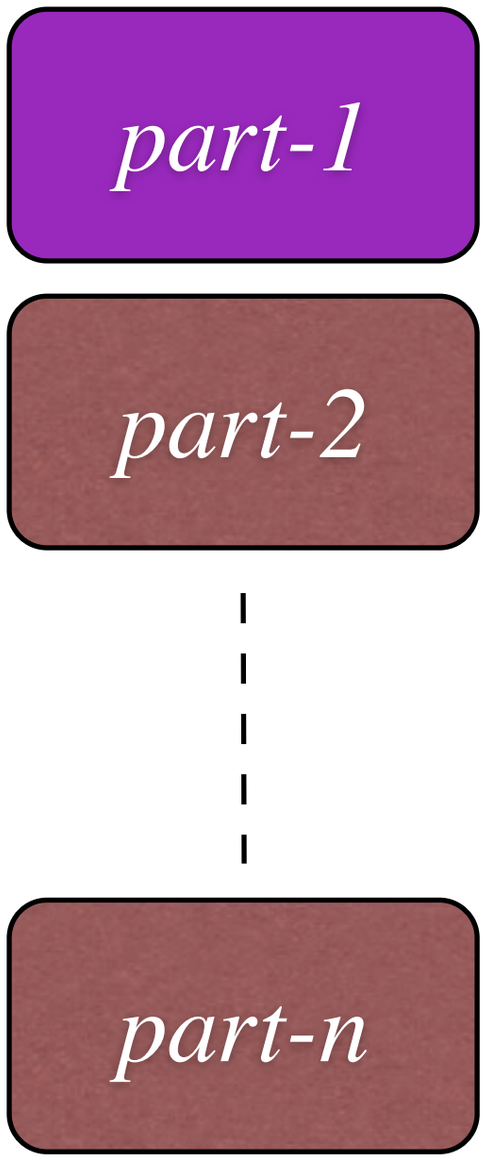

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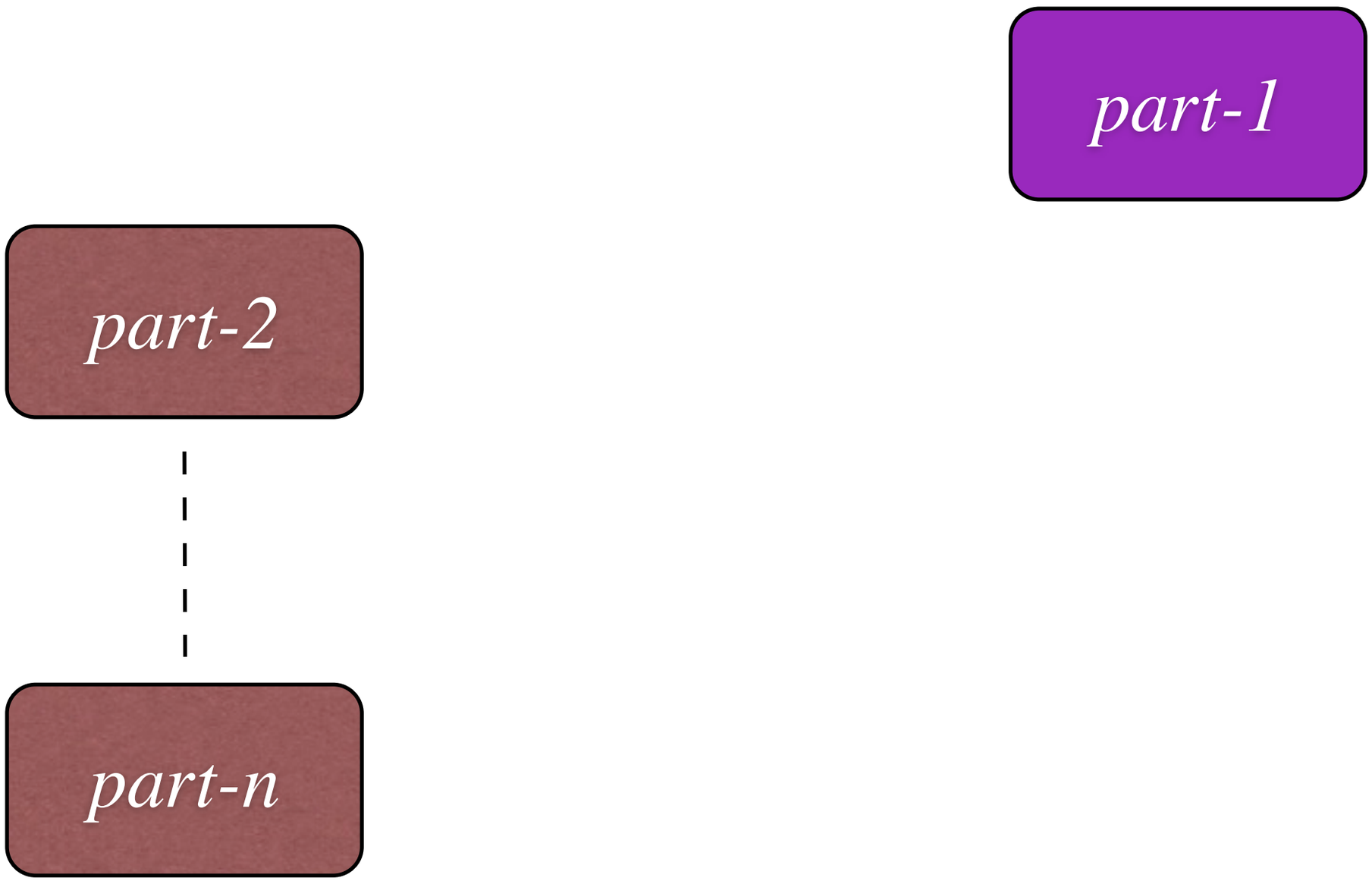

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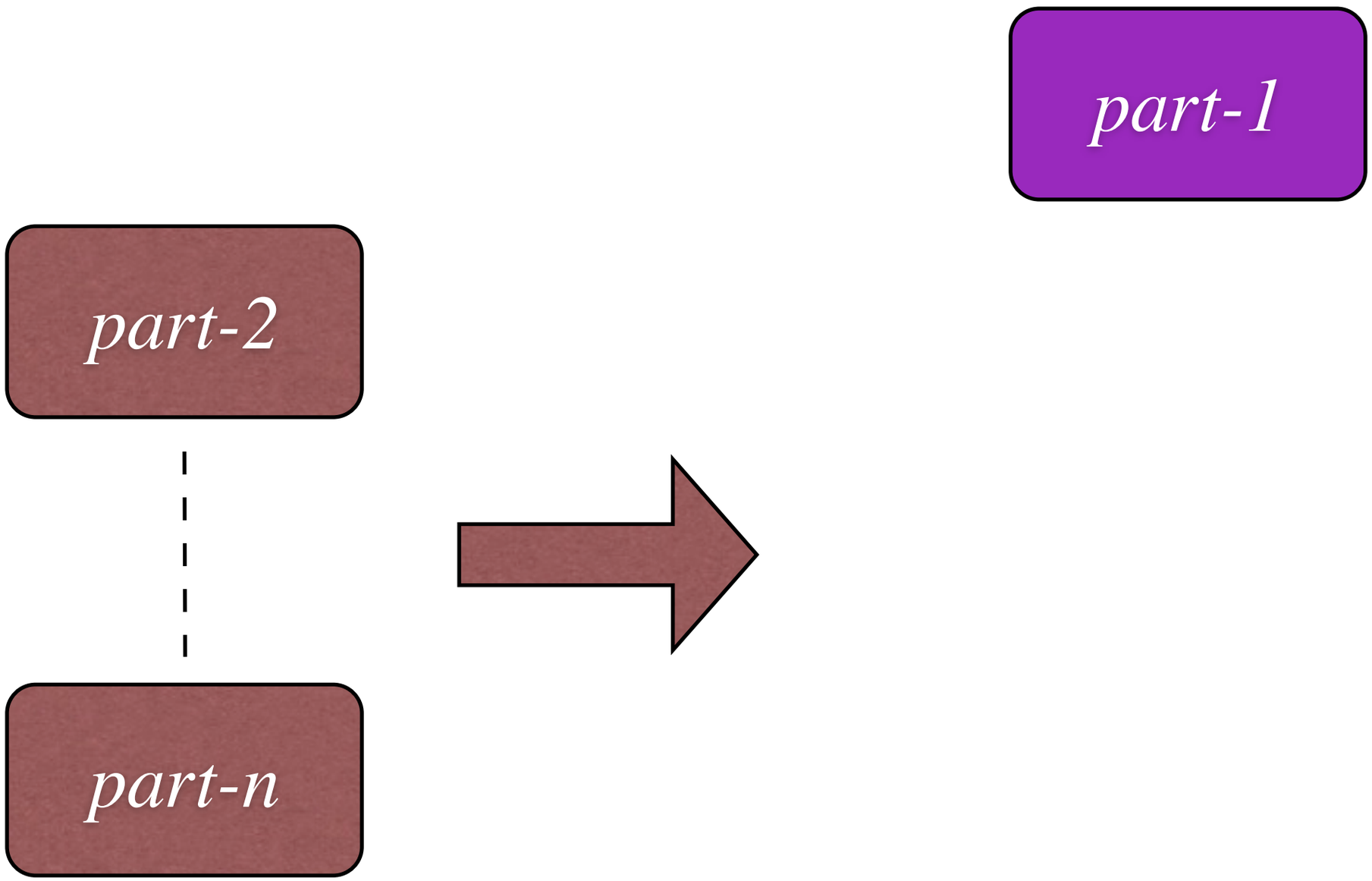

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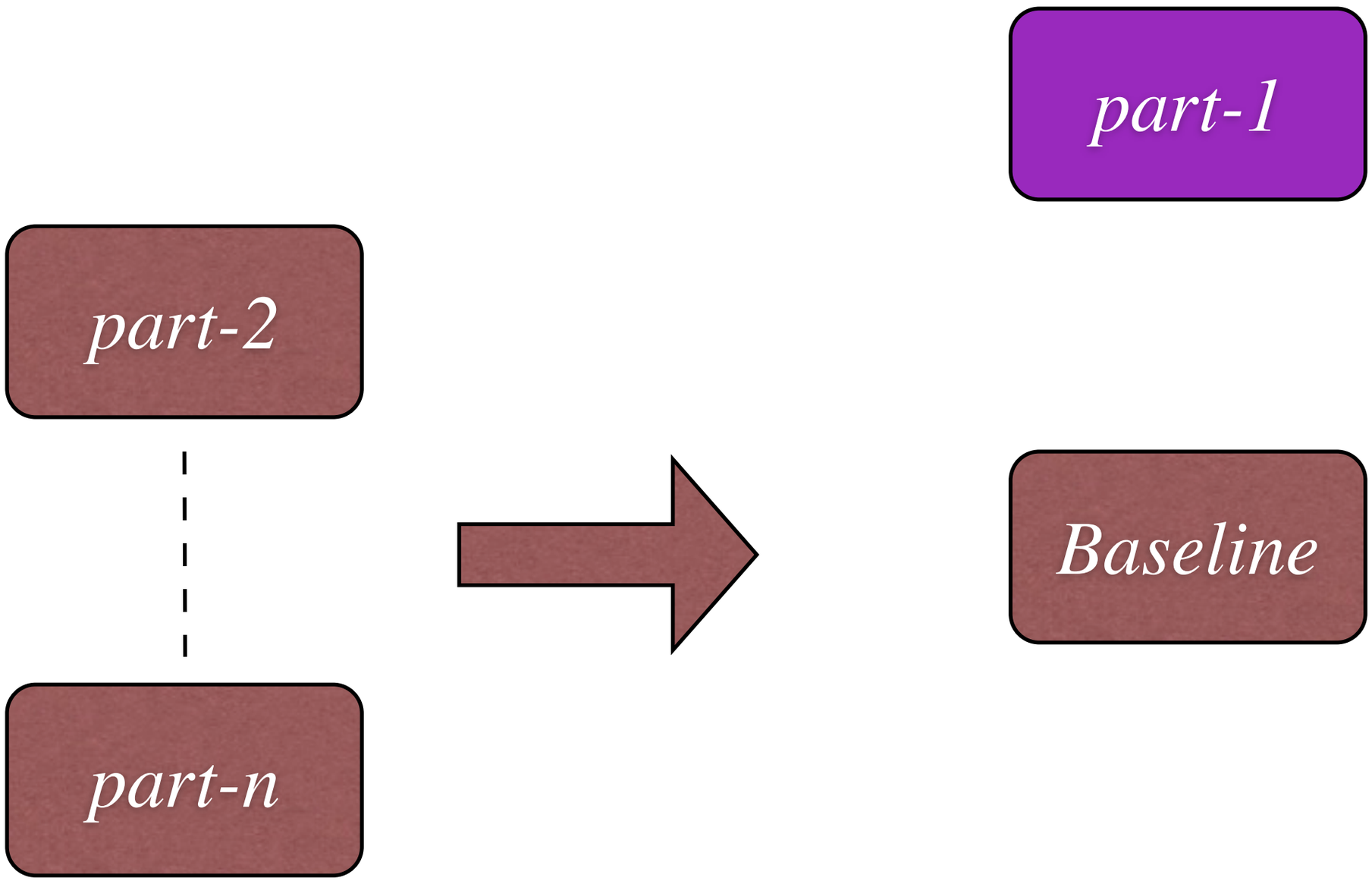

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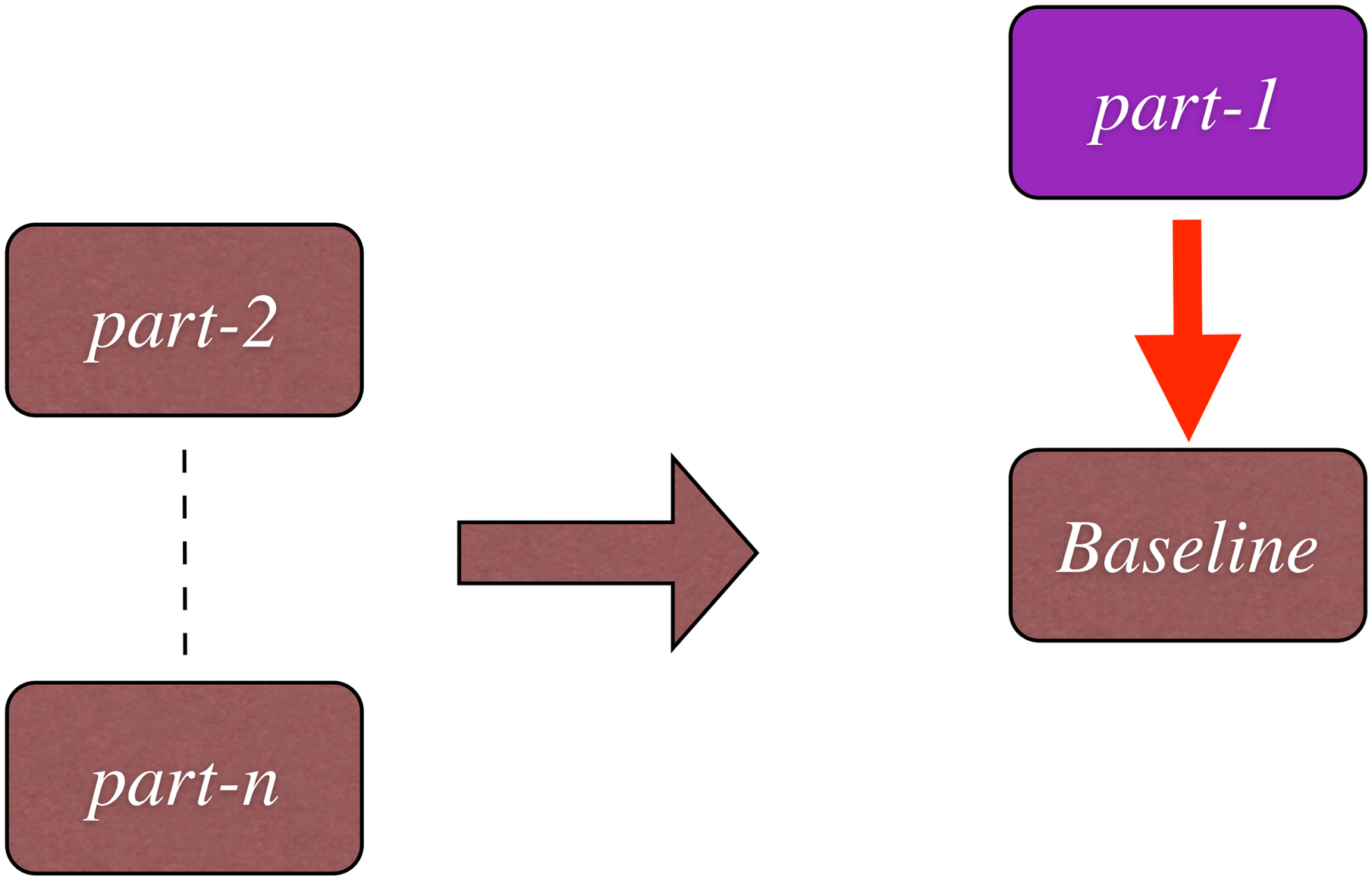

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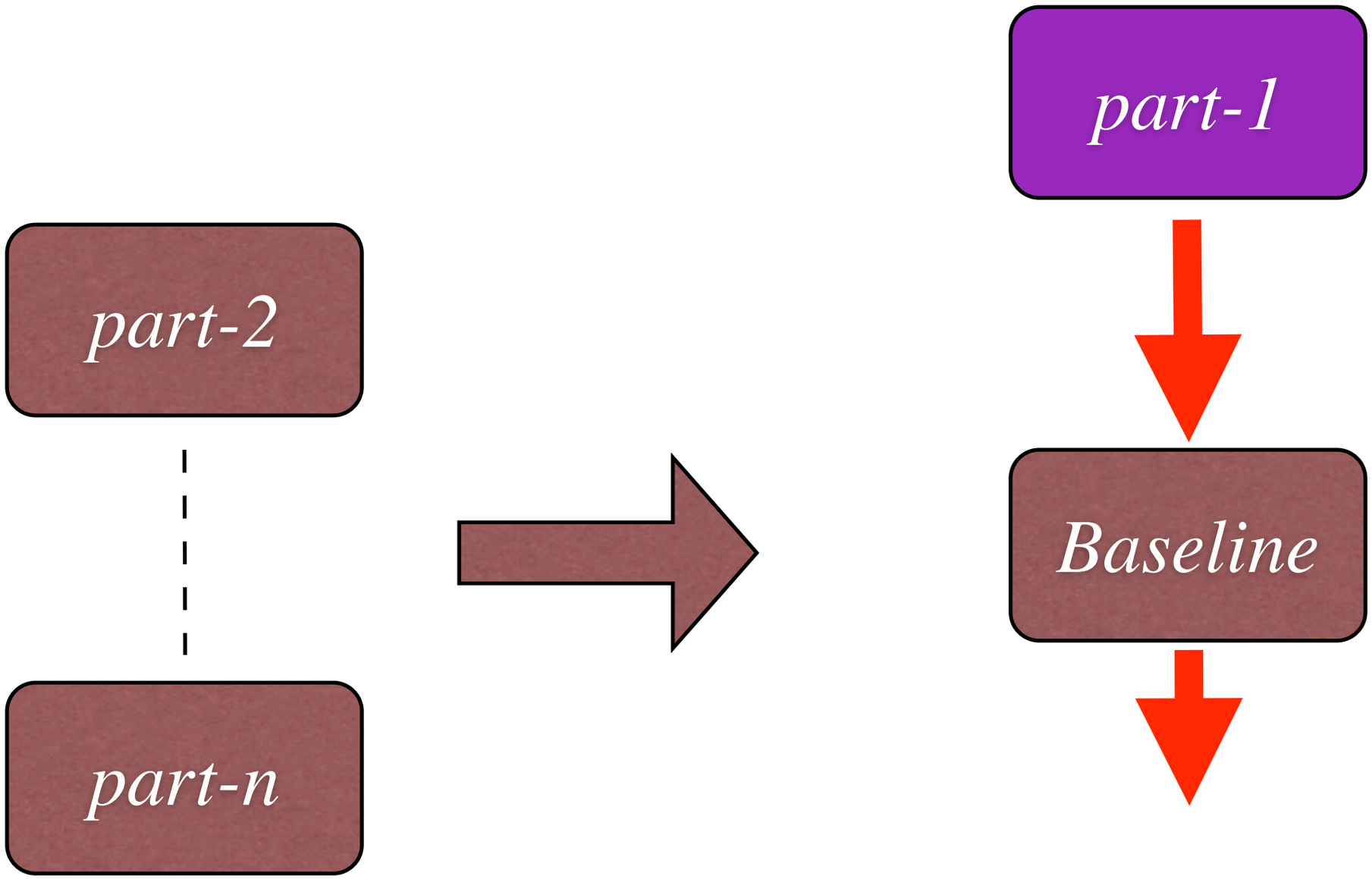

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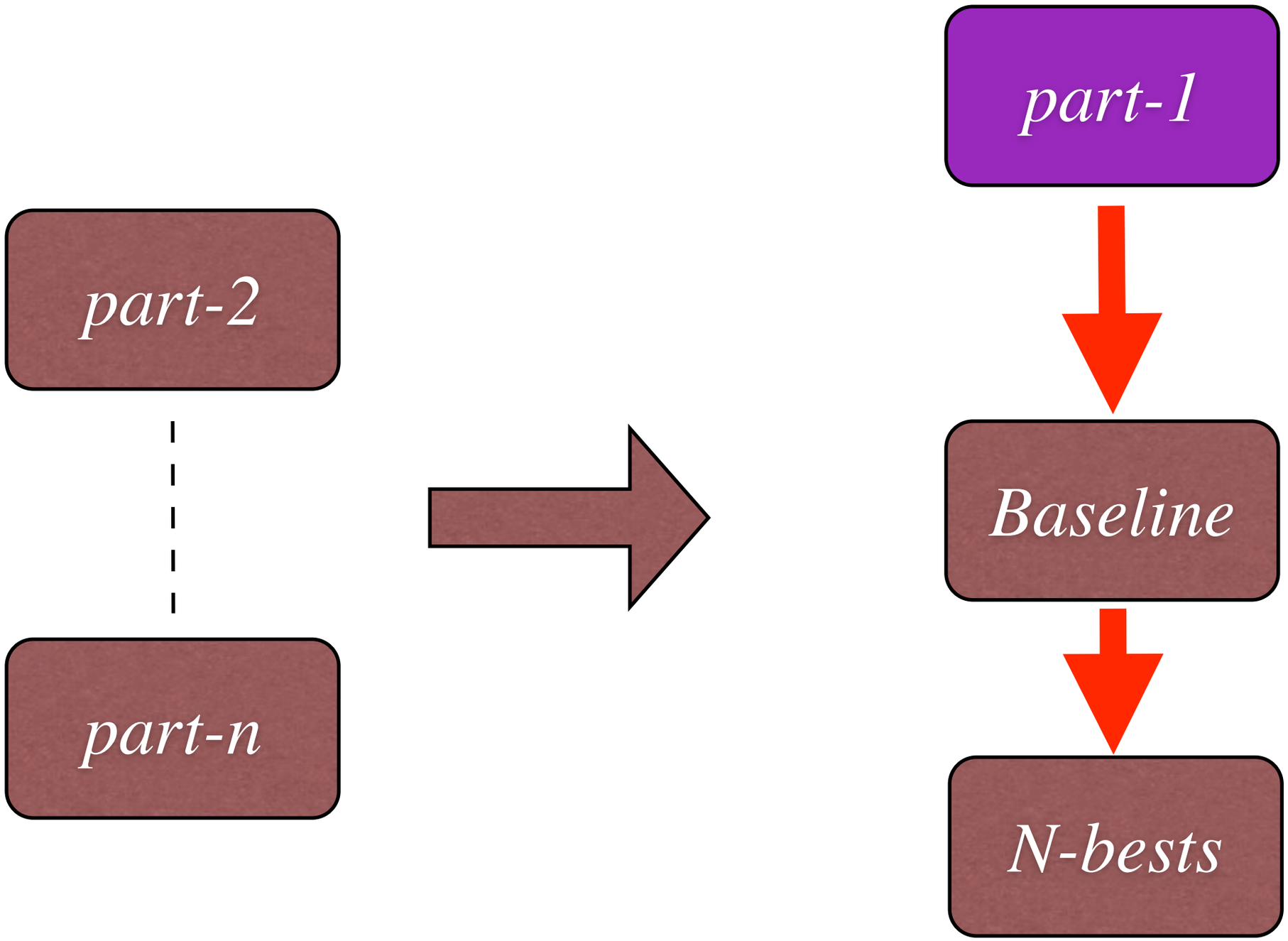

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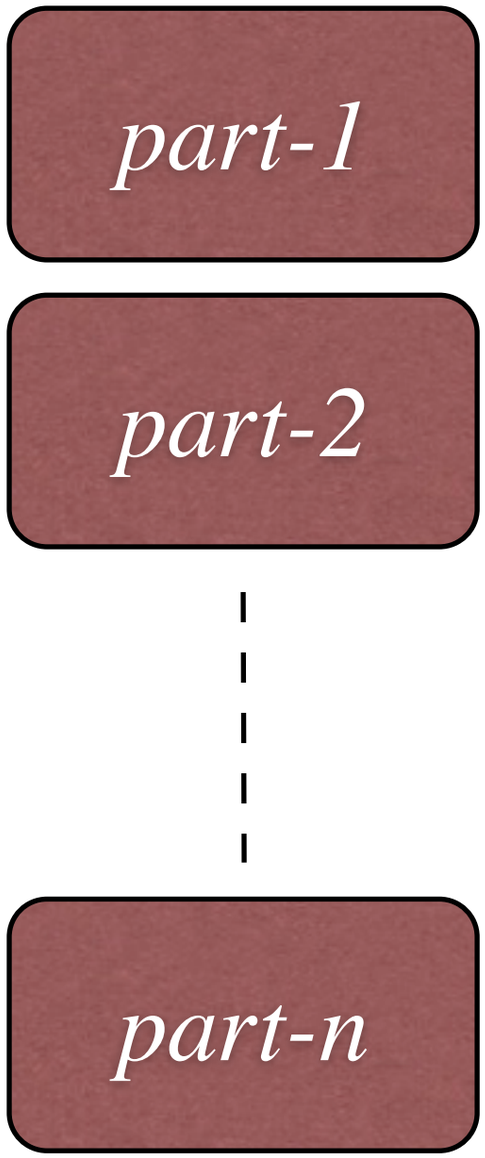

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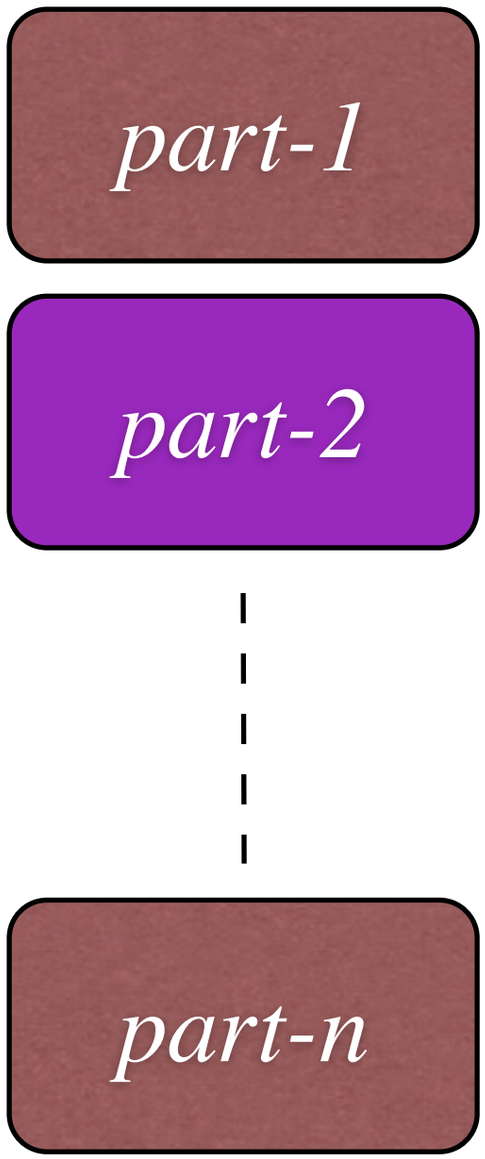

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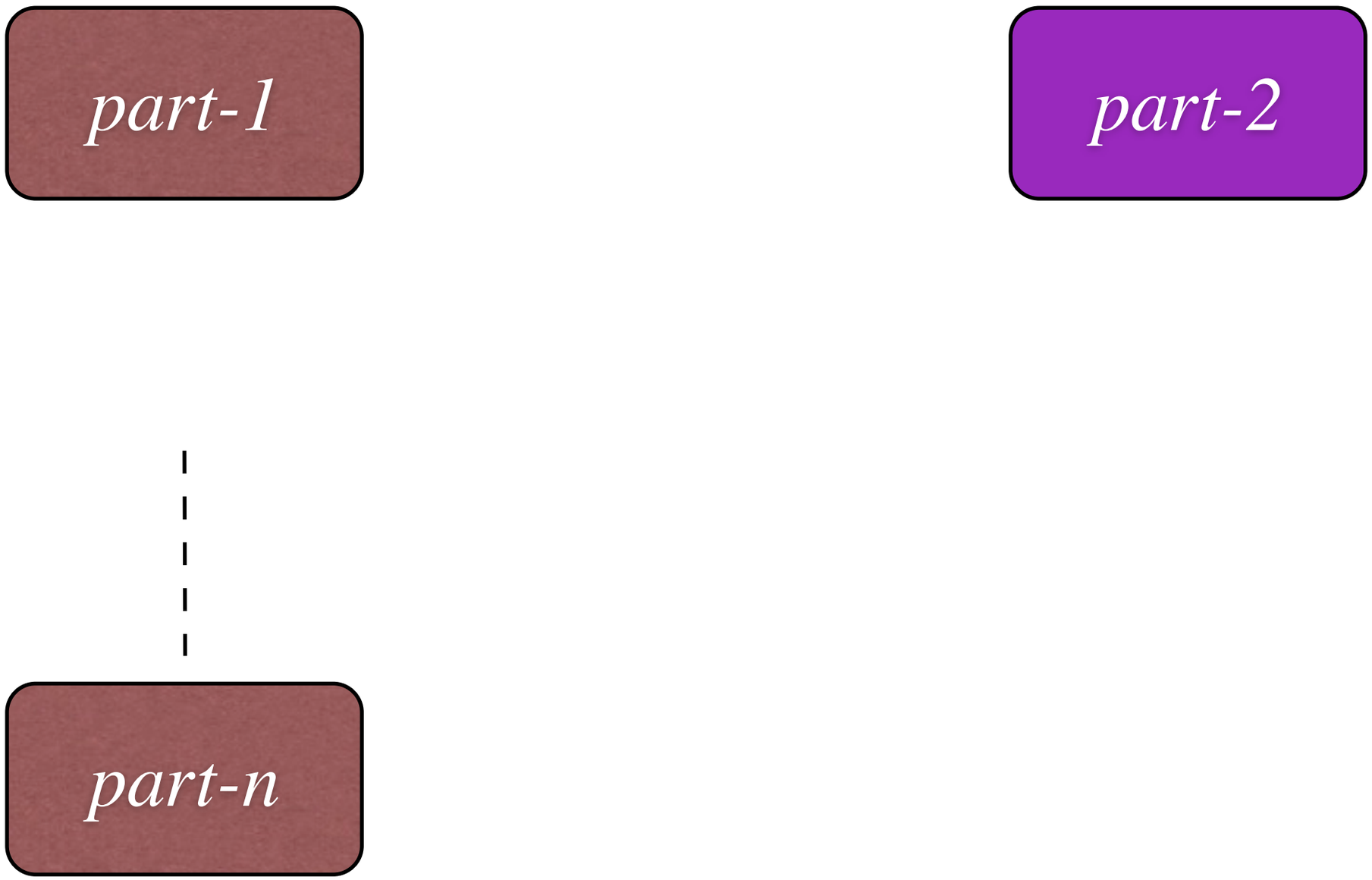

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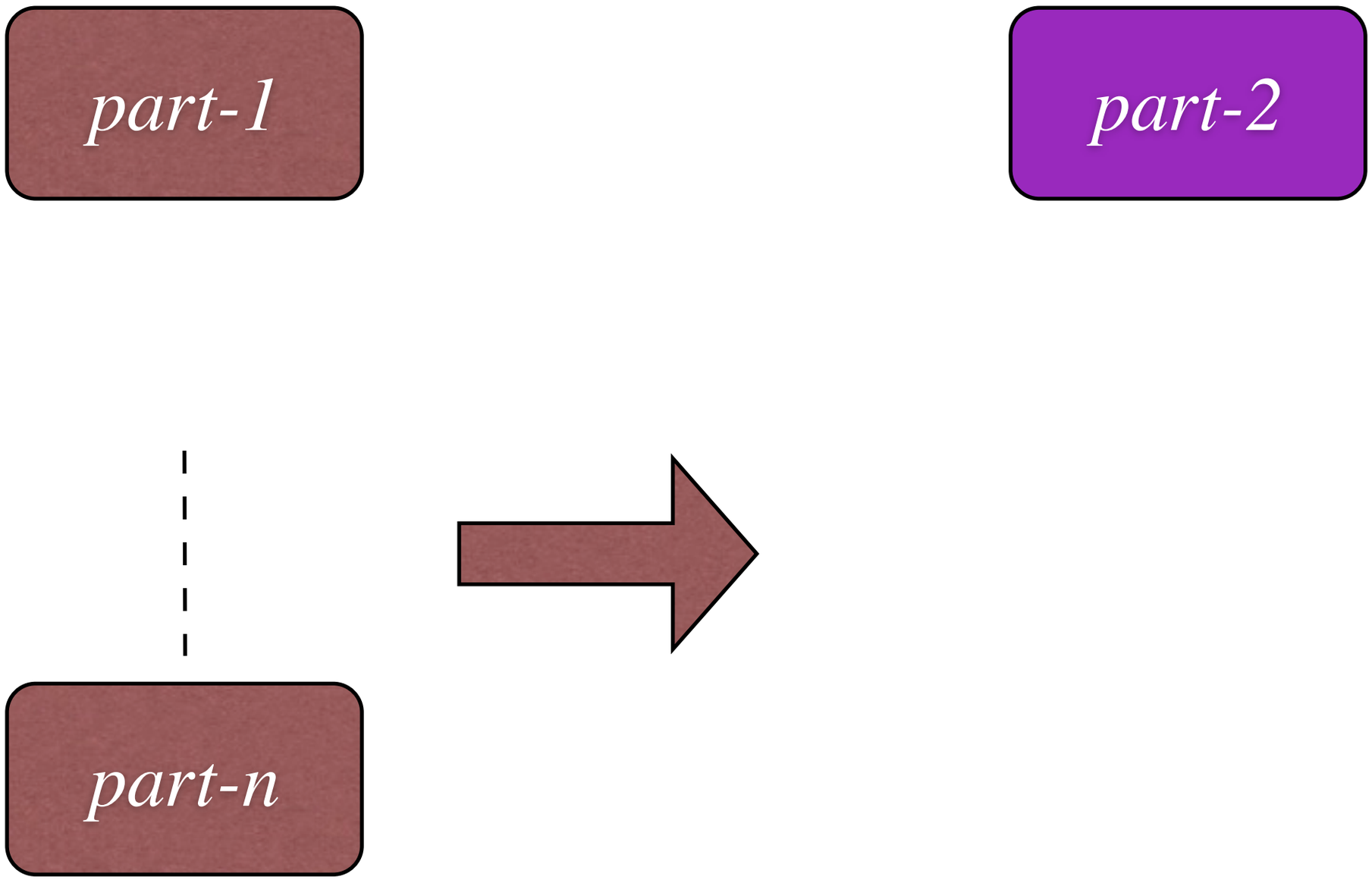

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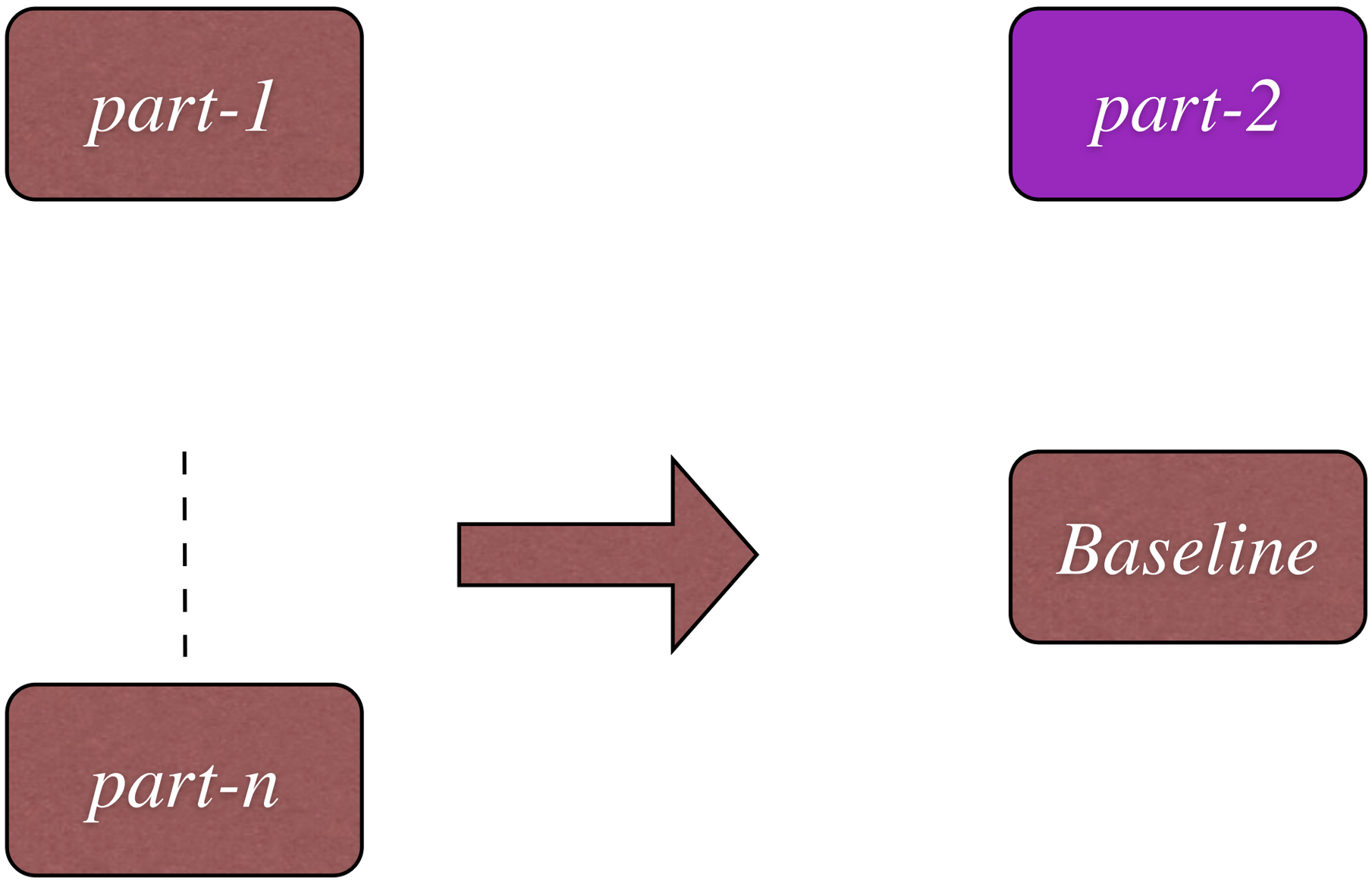

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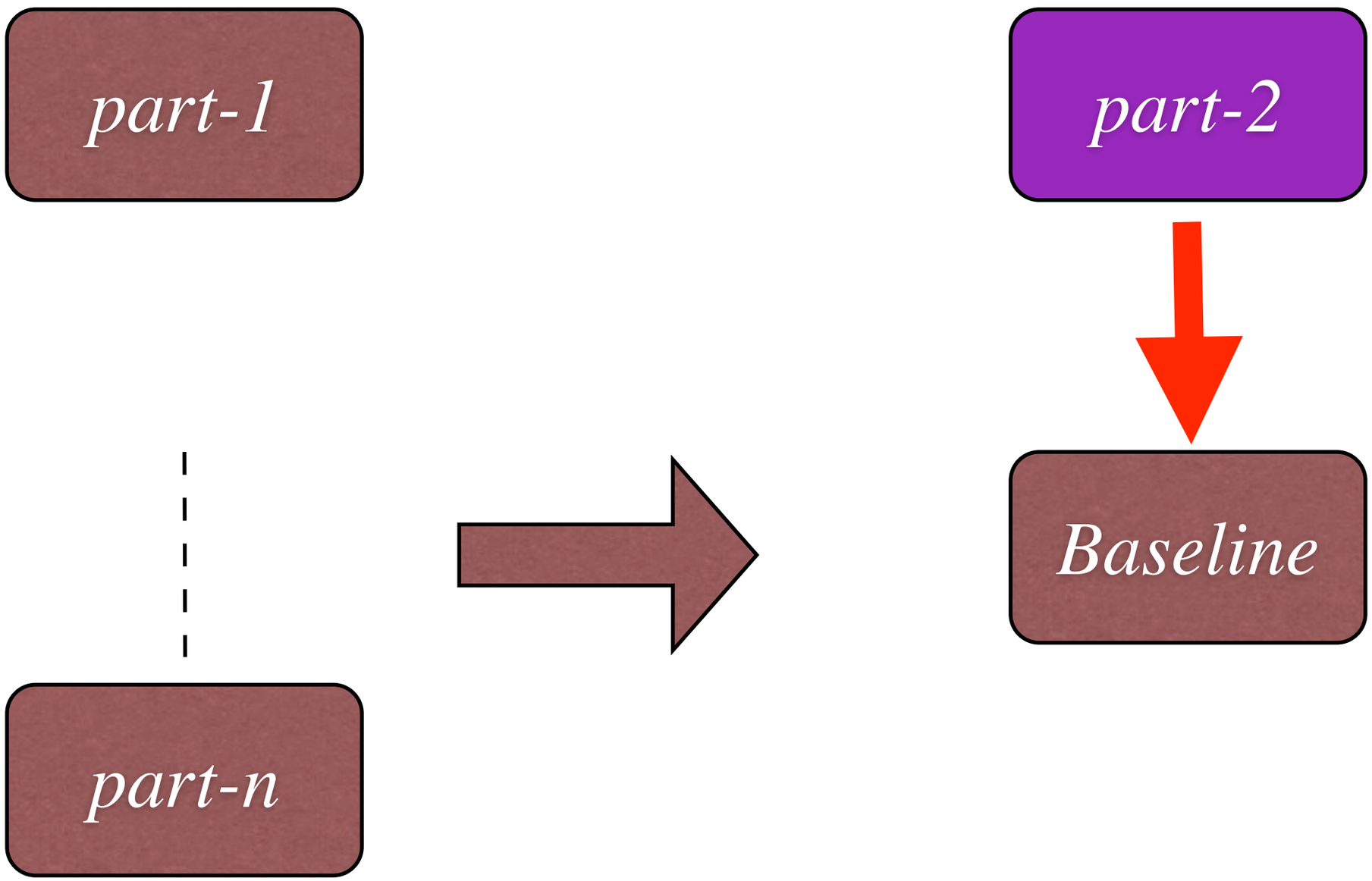

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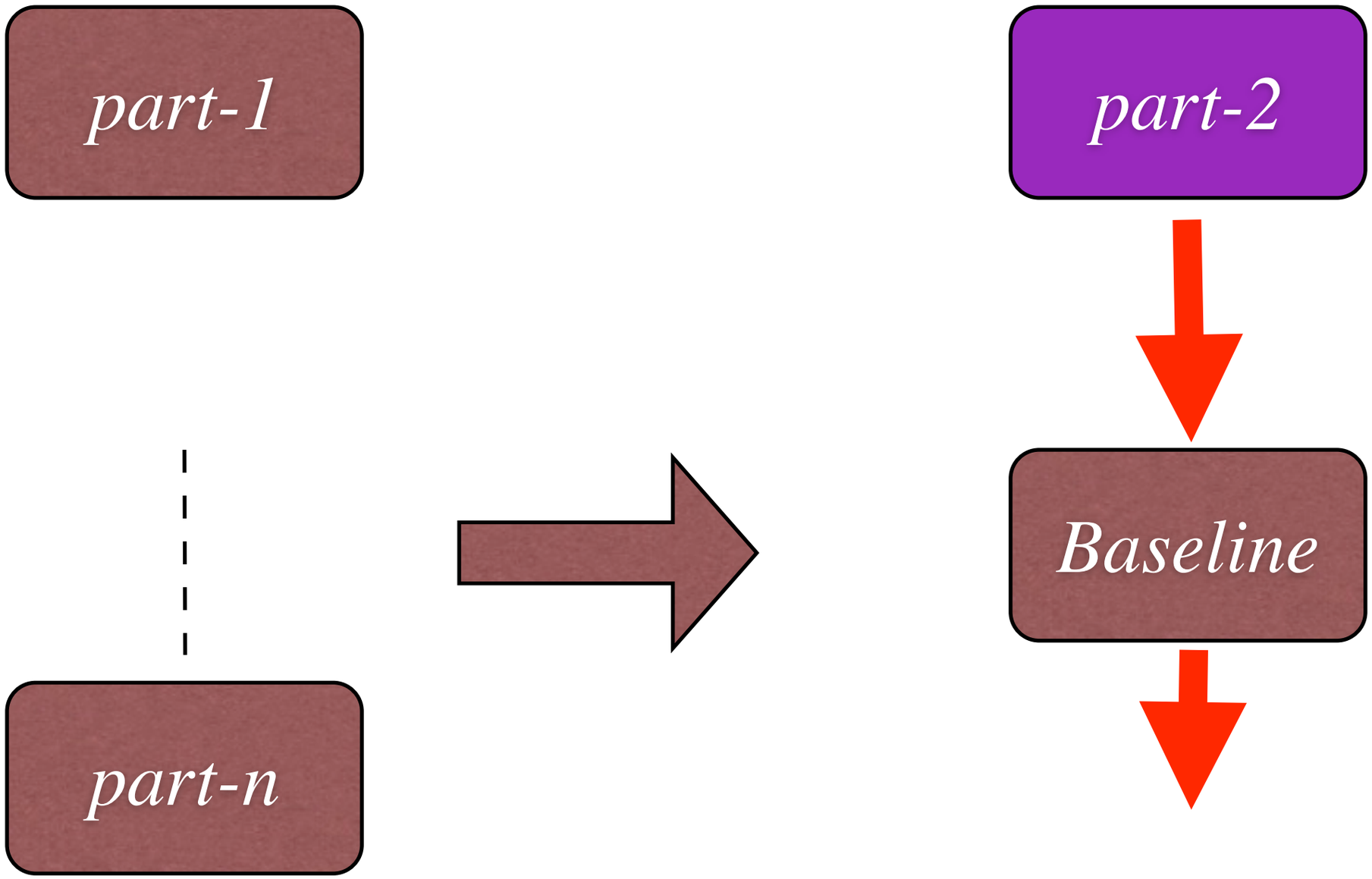

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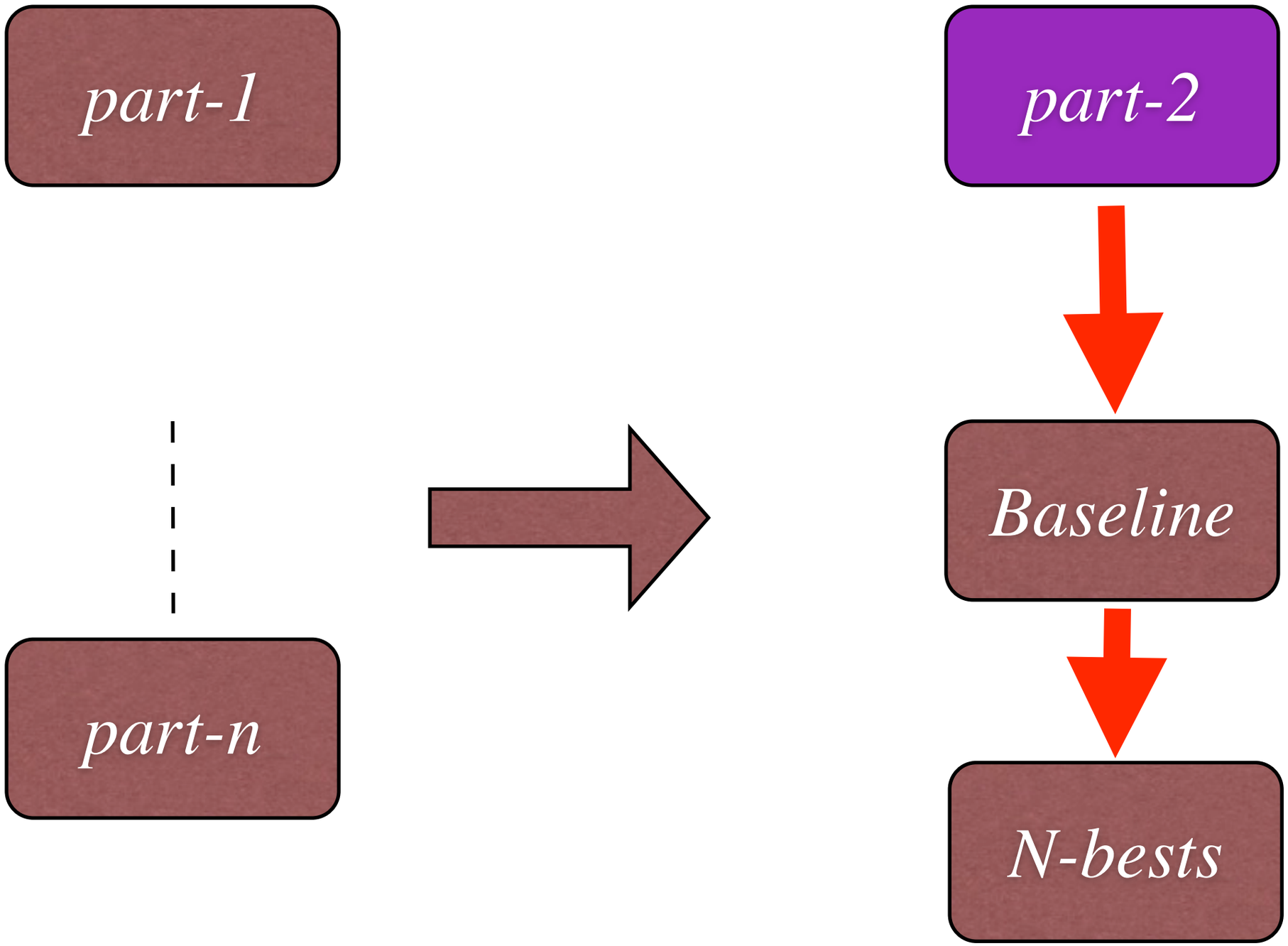

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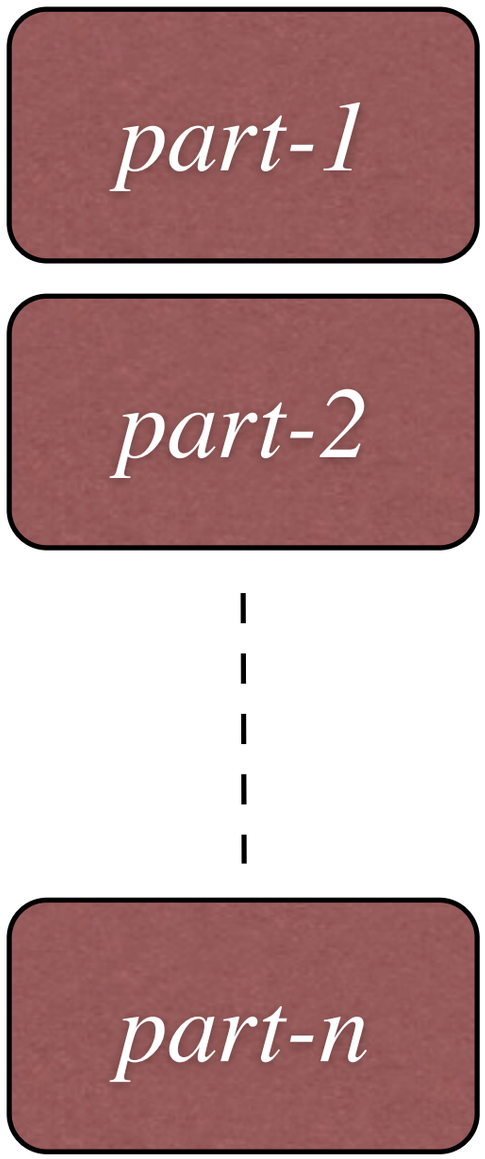

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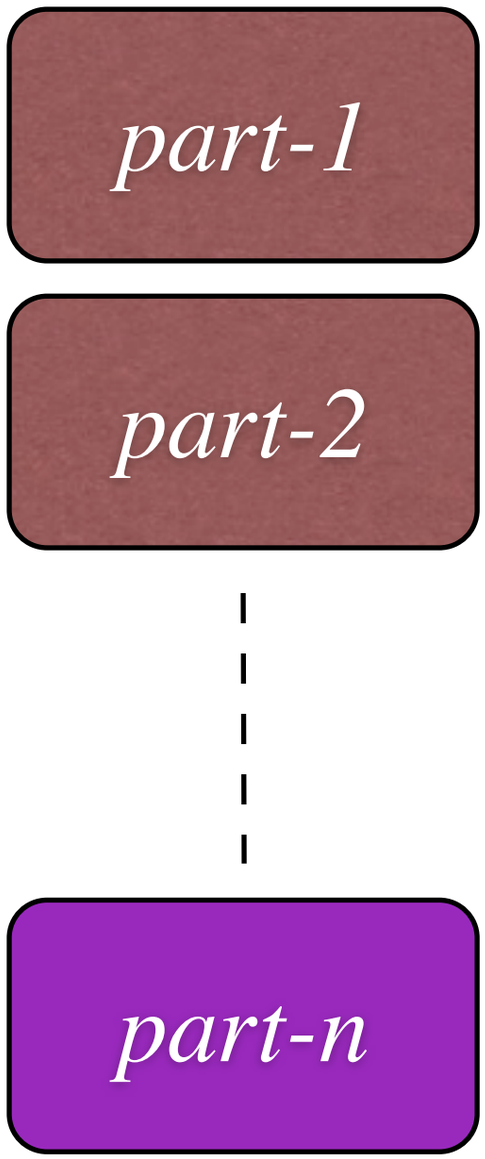

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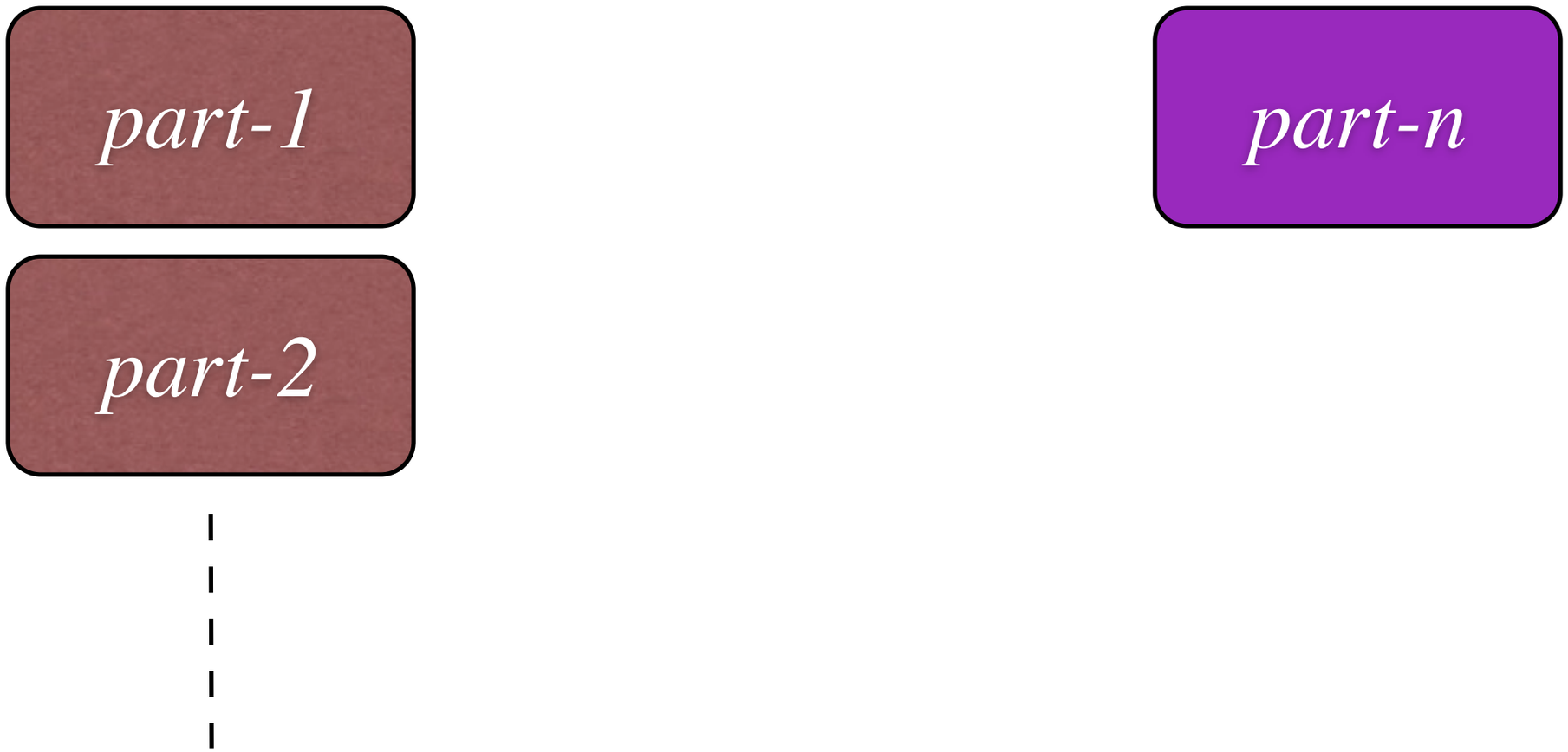

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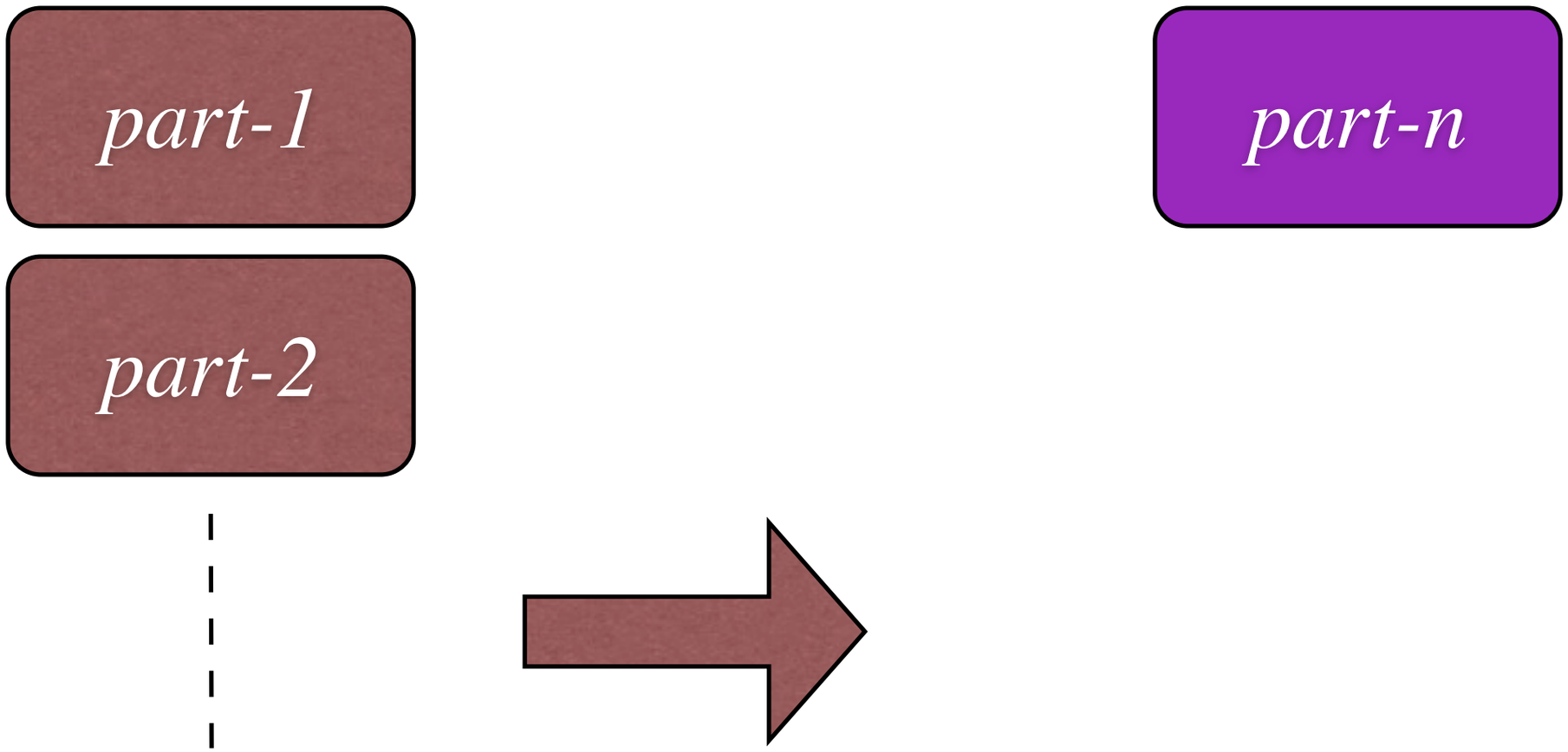

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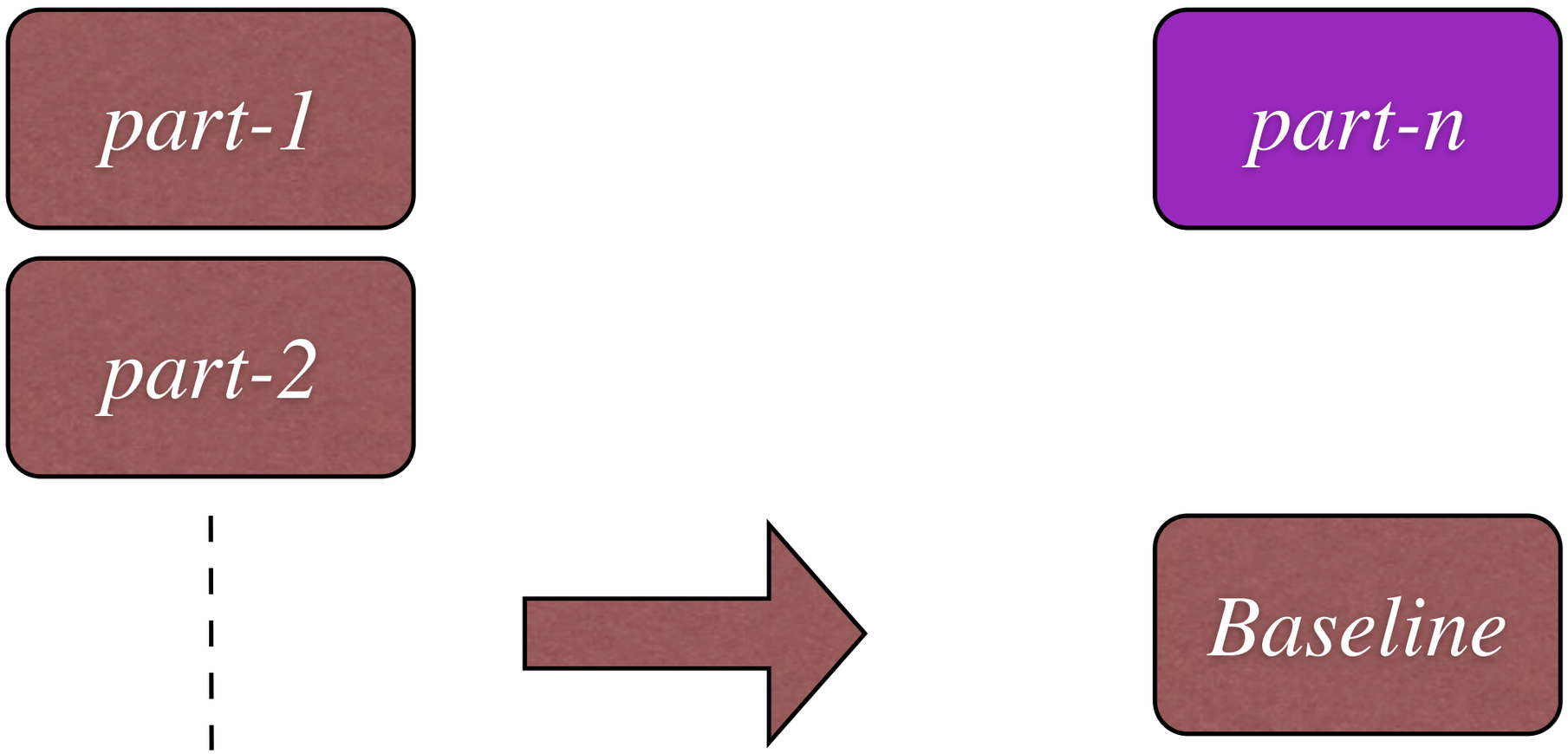

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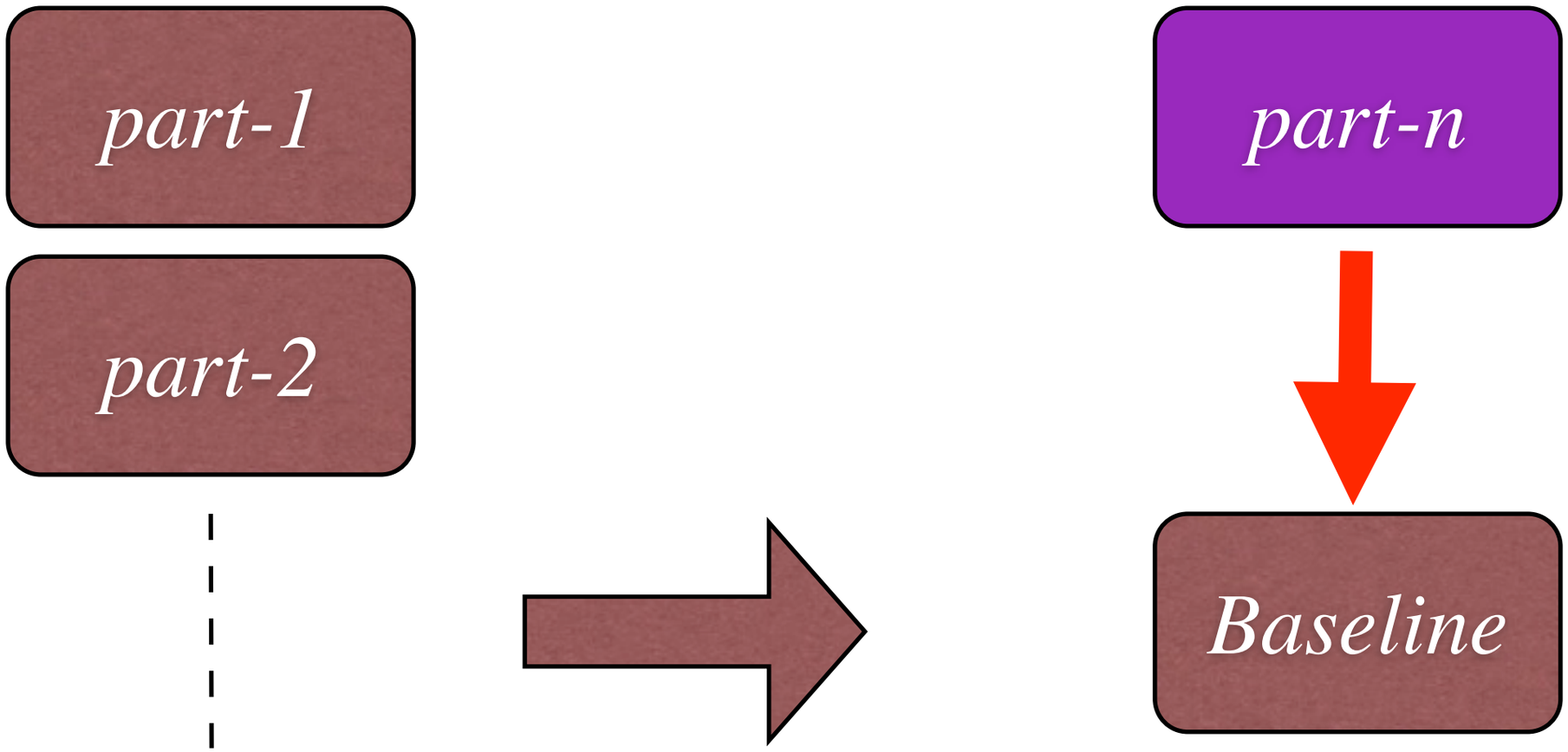

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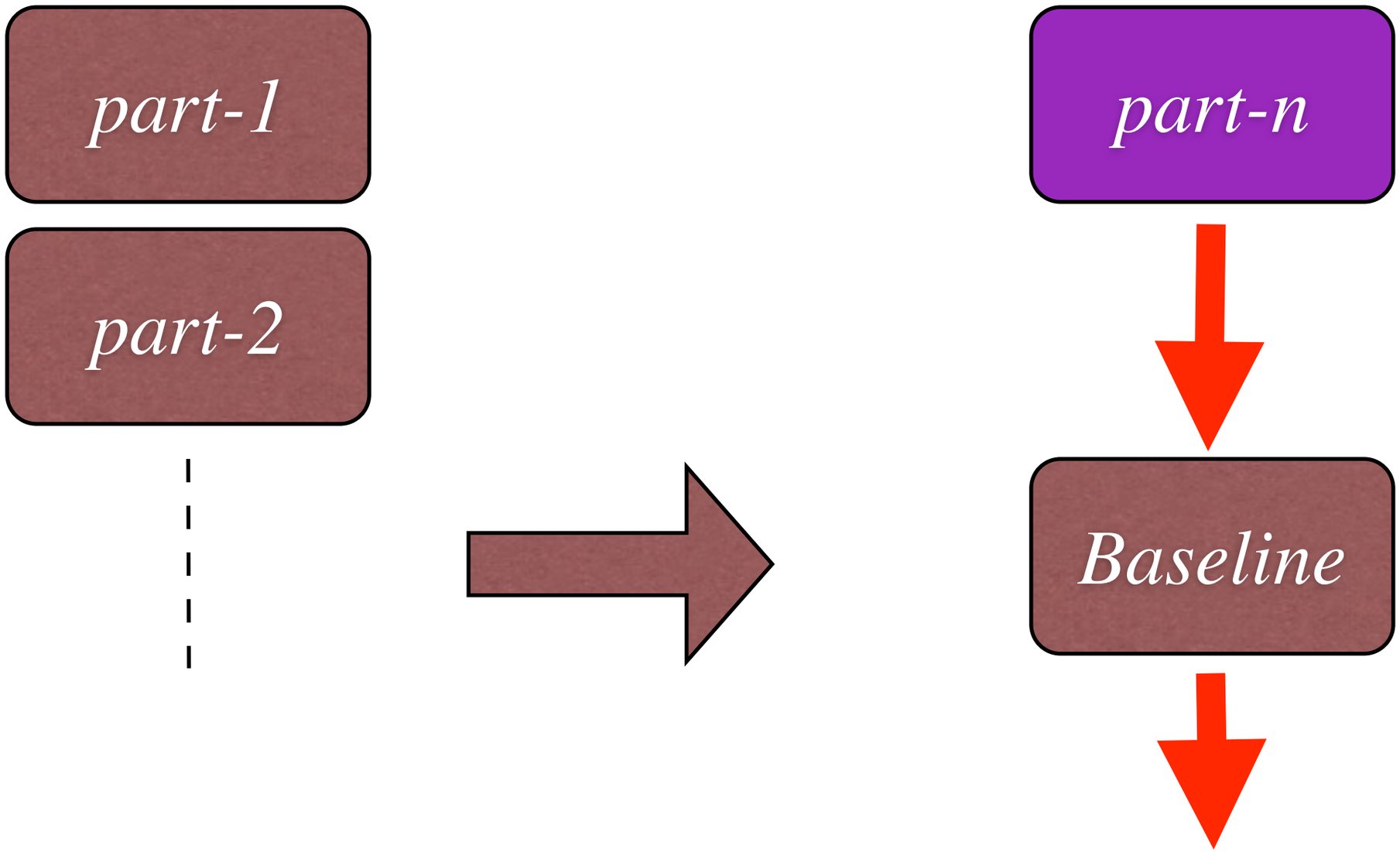

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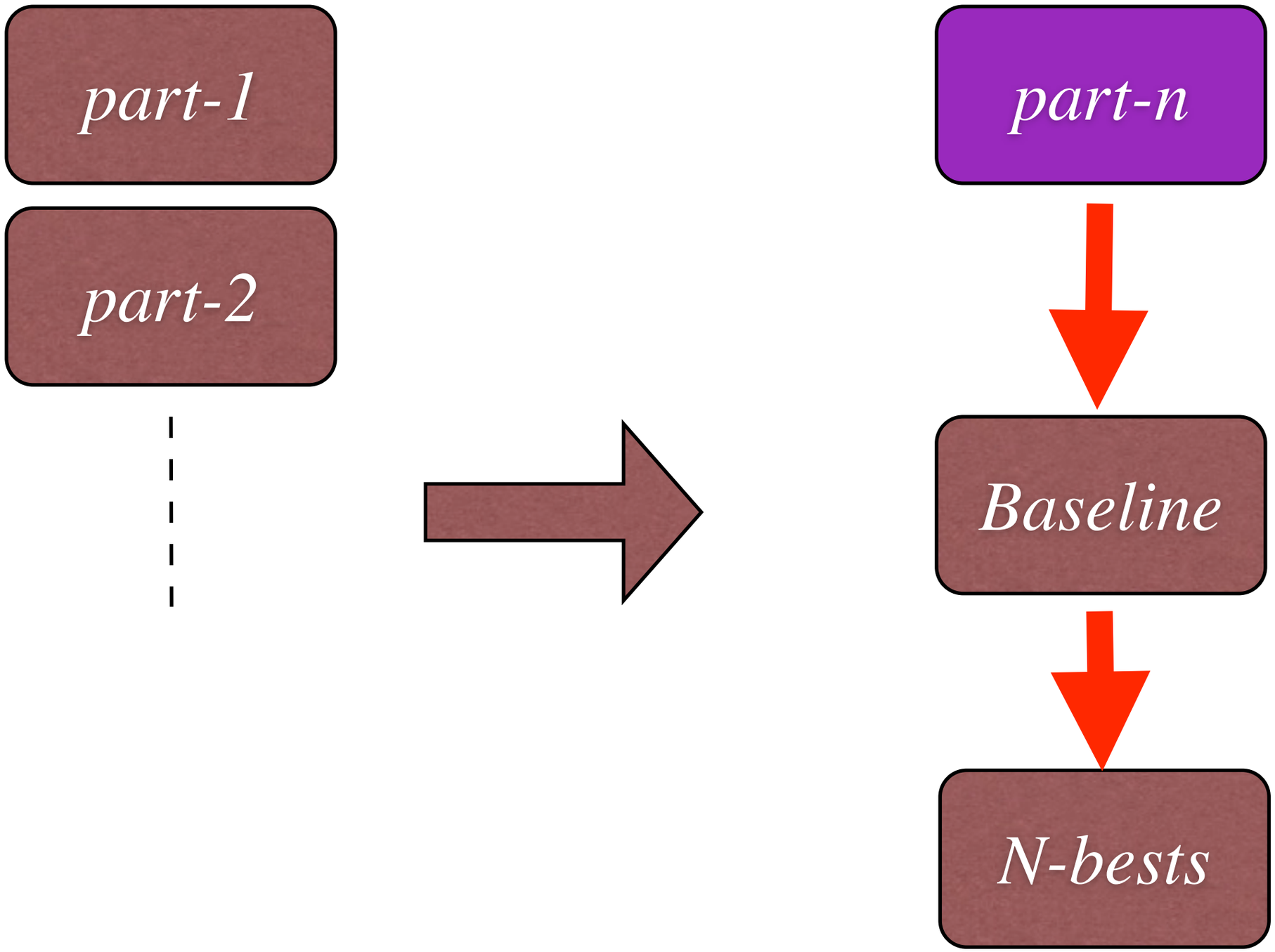

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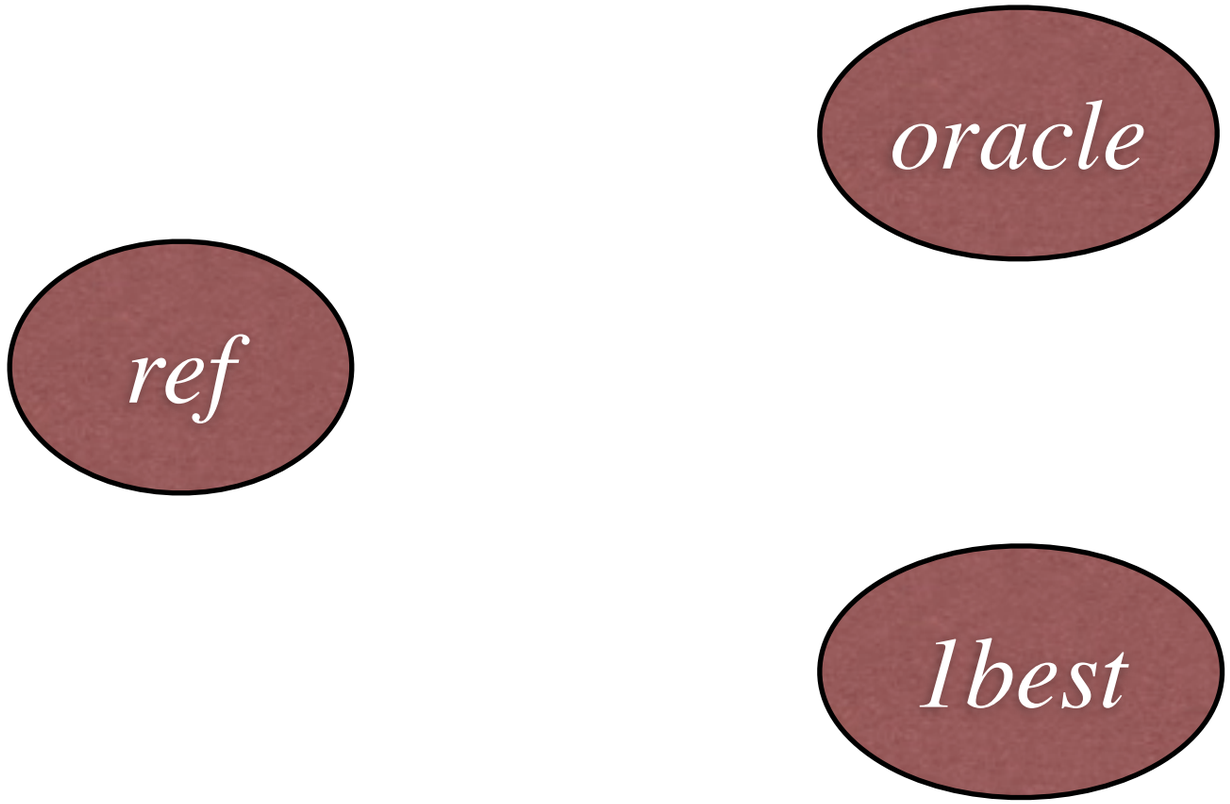
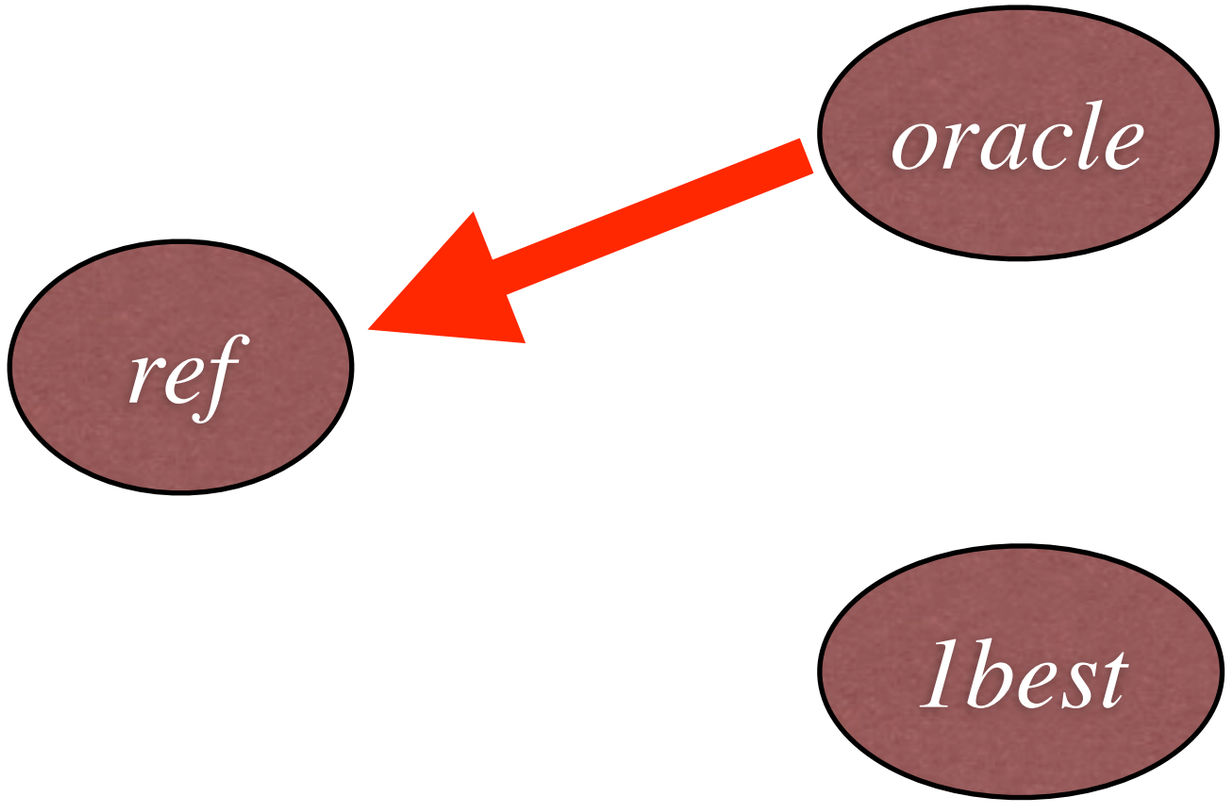
  - An training example will be selected only if it satisfies certain conditions


oracle
ref
1best



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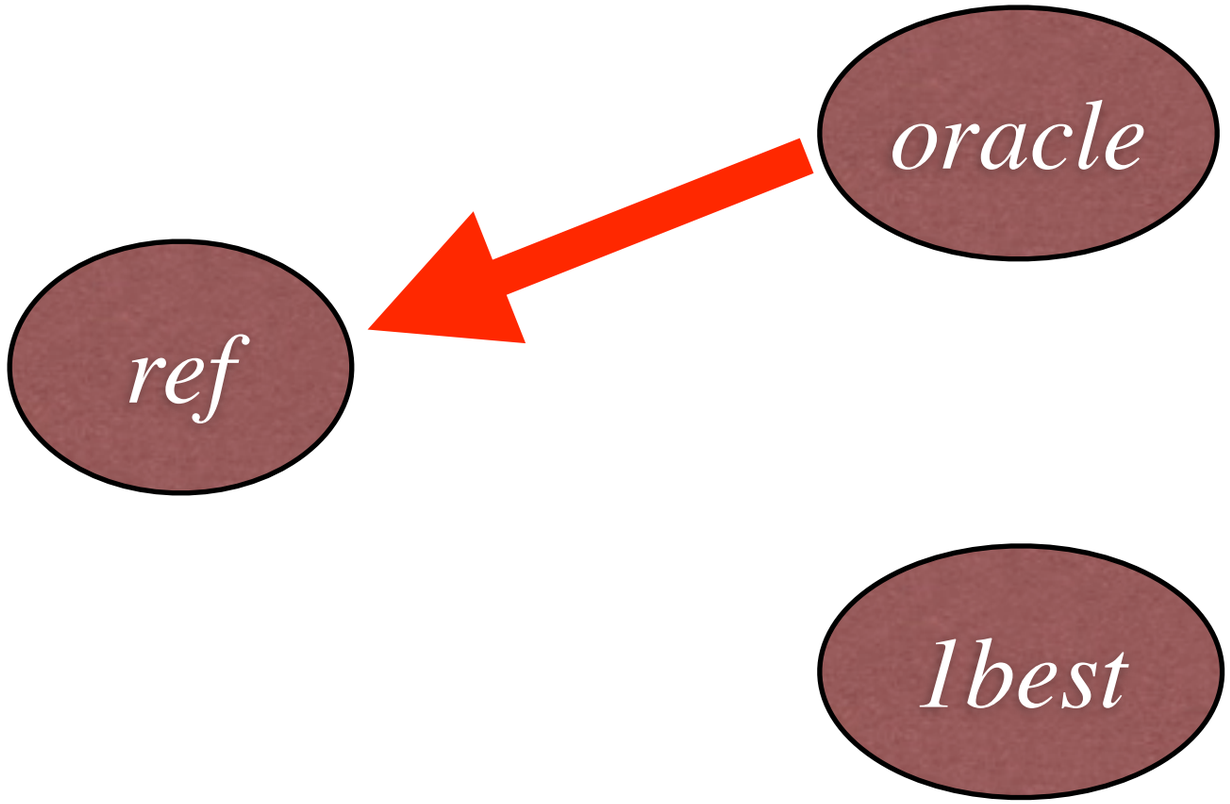

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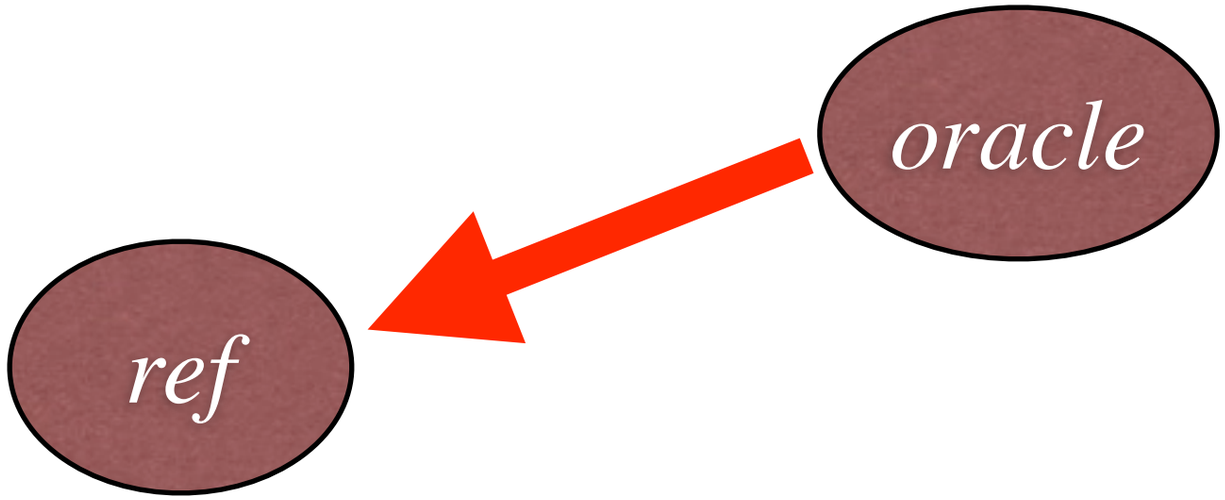

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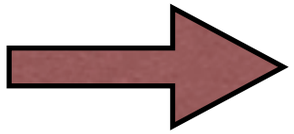

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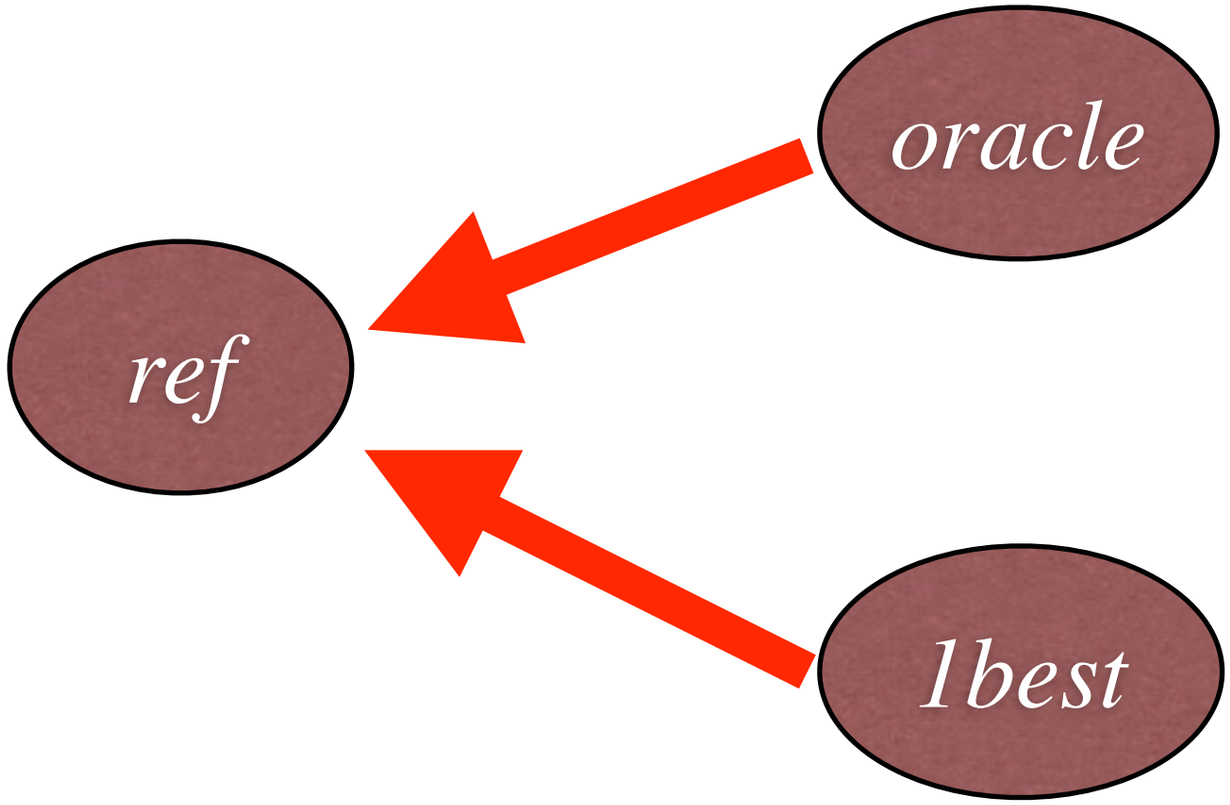

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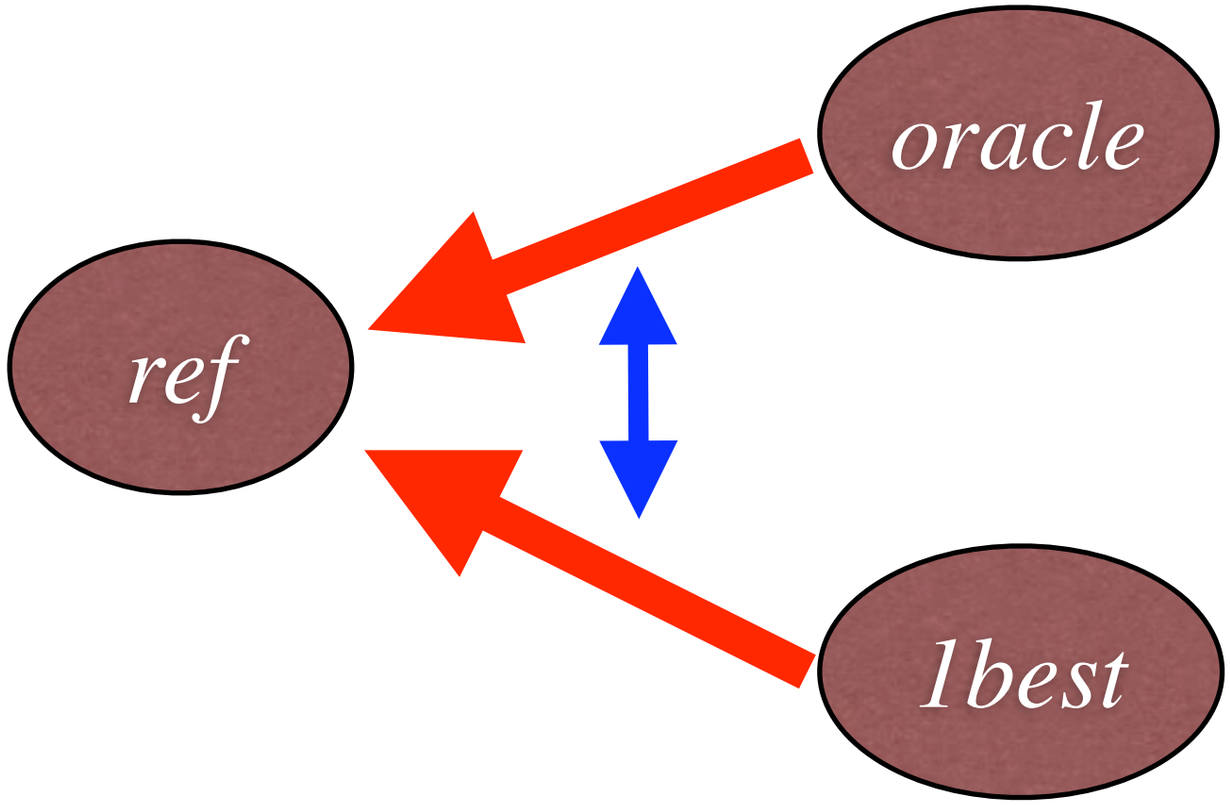

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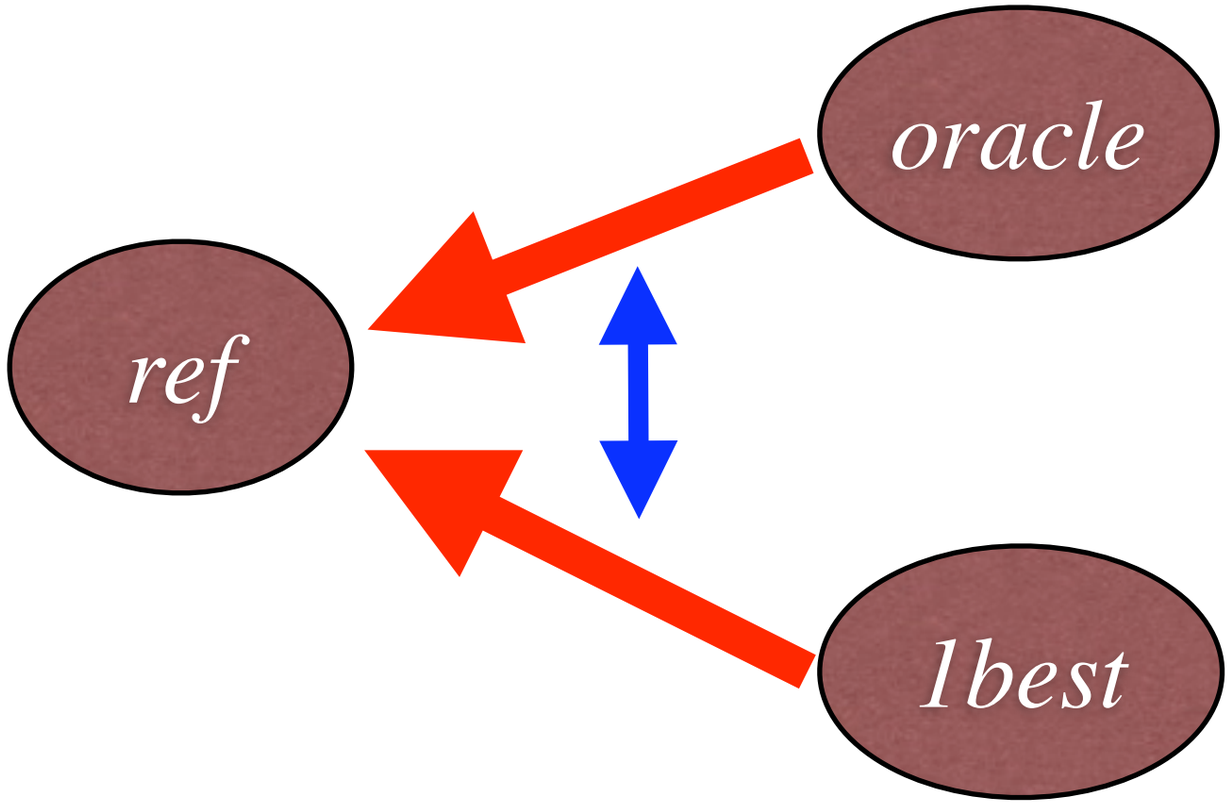
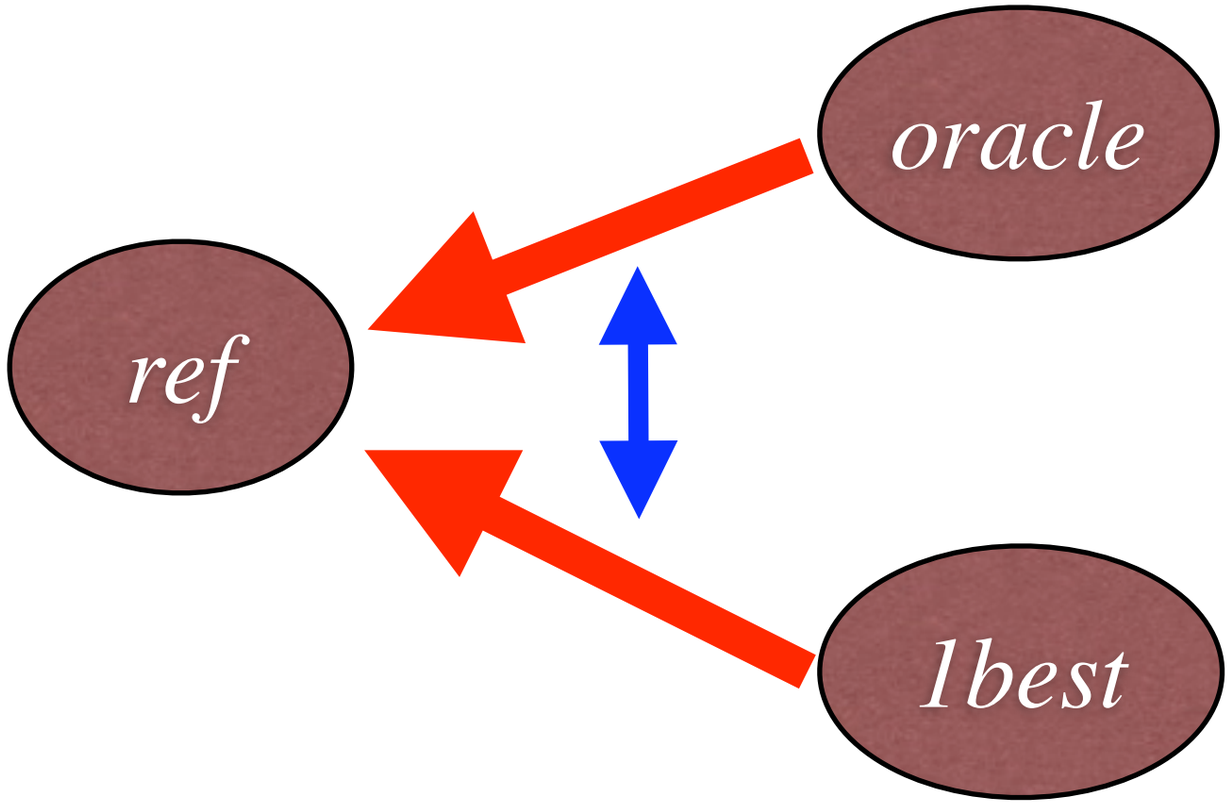


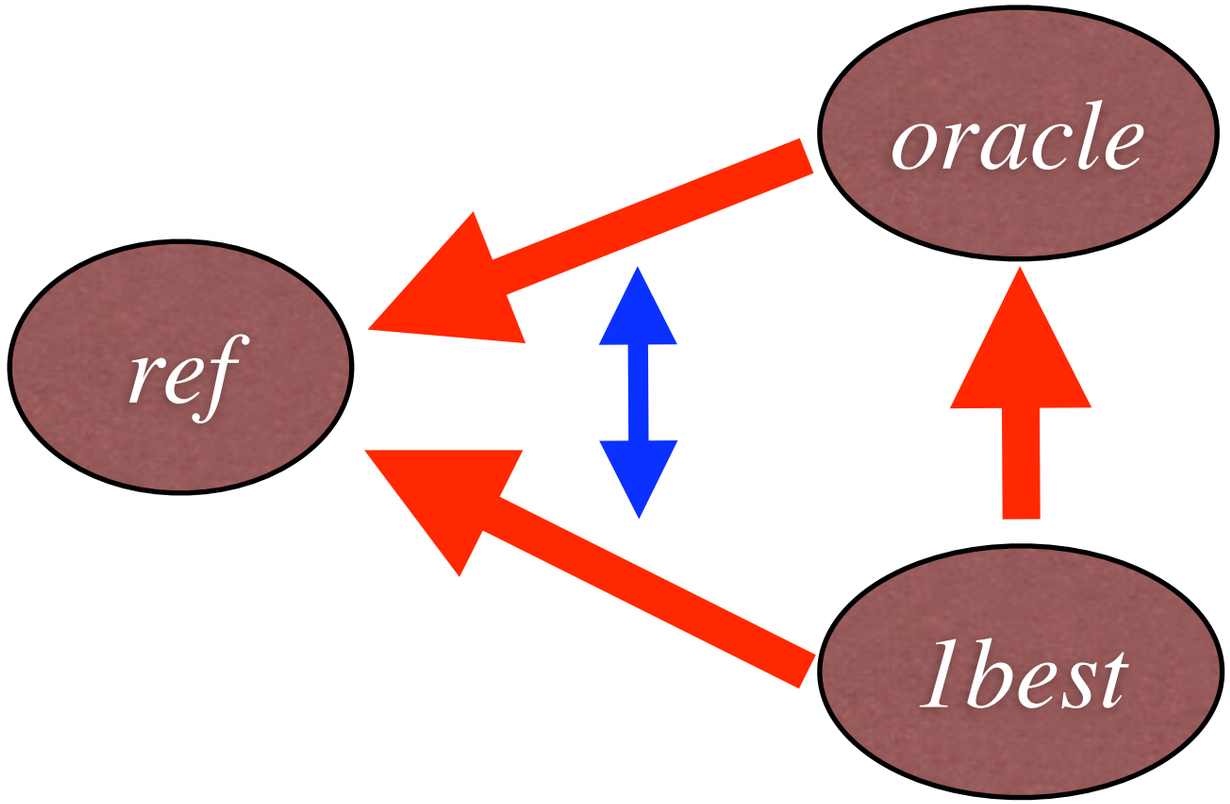
$$\mathbf{G(ref, oracle) > T_1}$$ → *matched translation*

$$\mathbf{G(ref, oracle) - G(ref, 1best) > T_2}$$ →



$$\mathbf{G(ref, oracle) > T_1}$$ → *matched translation*

$$\mathbf{G(ref, oracle) - G(ref, 1best) > T_2}$$ → *profitable*



$$\mathbf{G(ref, oracle) > T_1}$$ → *matched translation*

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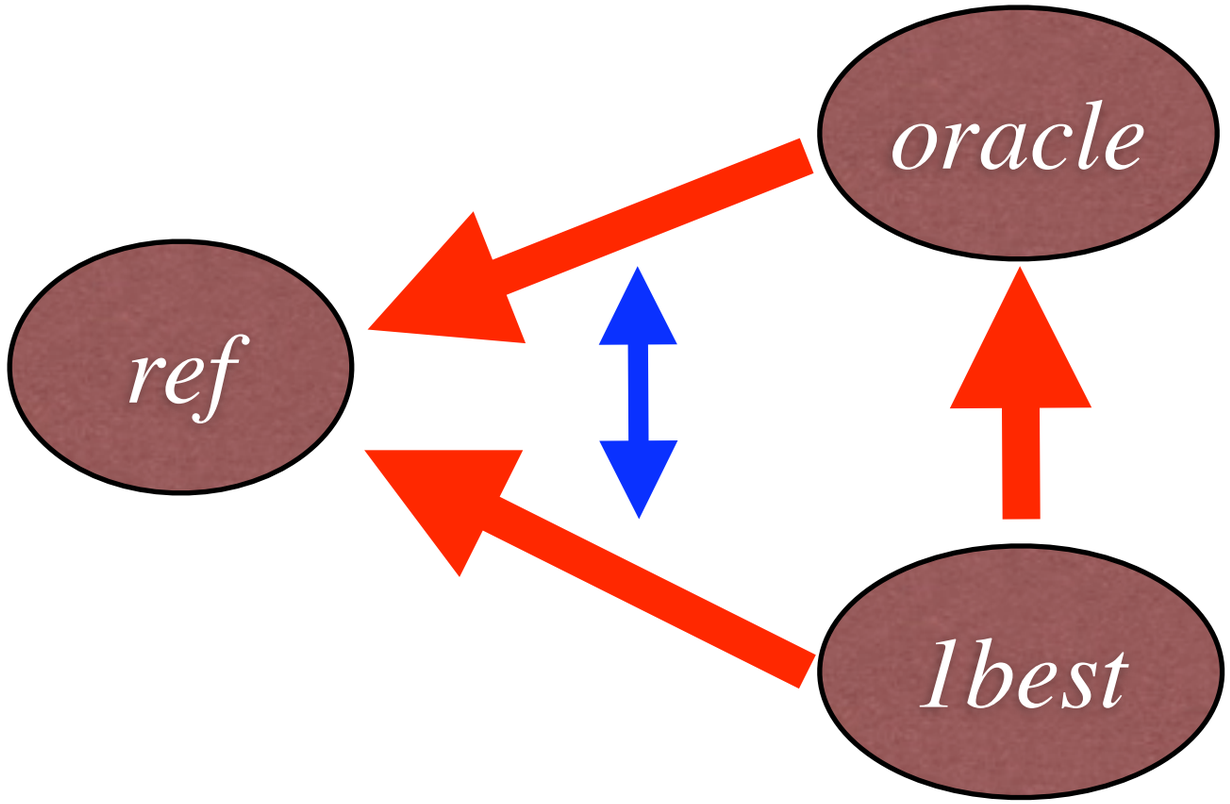
$$\mathbf{G(oracle, 1best) > T_3}$$



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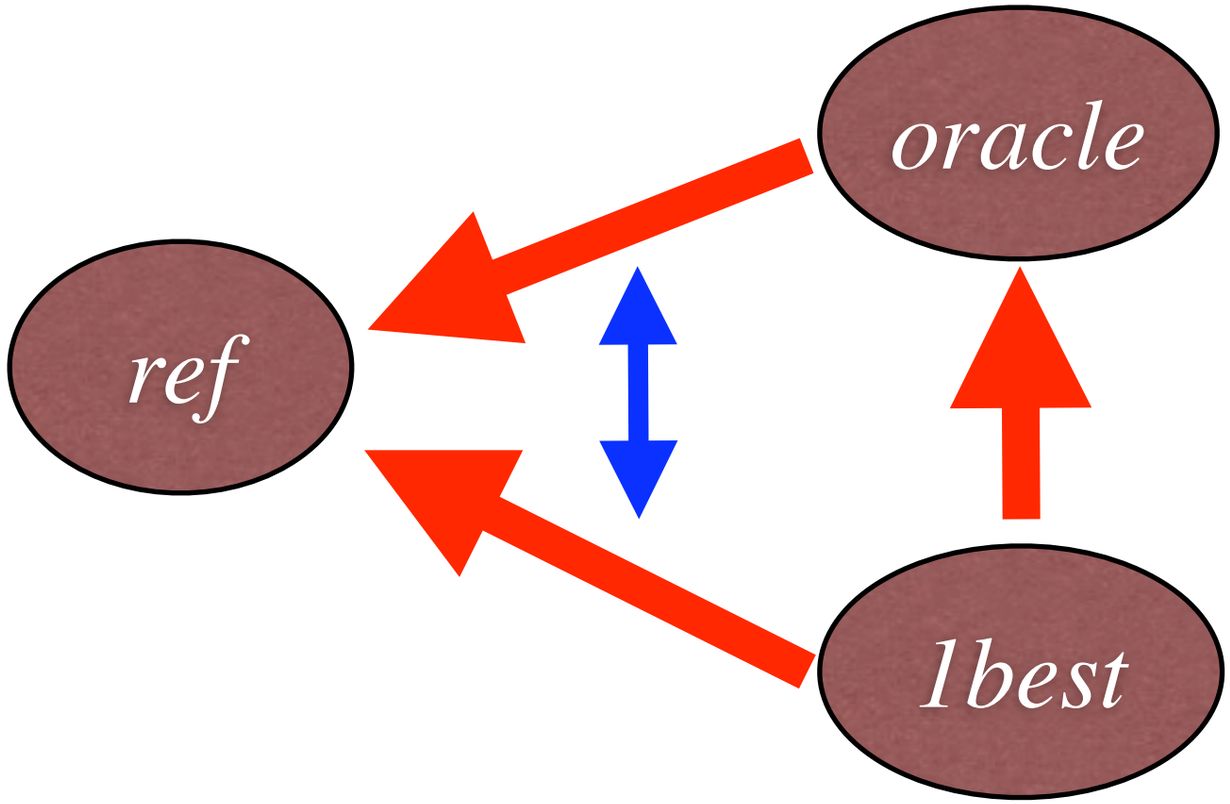

$$\mathbf{G(ref, oracle) > T_1}$$ → *matched translation*

$$\mathbf{G(ref, oracle) - G(ref, 1best) > T_2}$$ → *profitable*

$$\mathbf{G(oracle, 1best) > T_3}$$ → *correctable*

Experiments: facts

Language pair	*Chinese to English*
Translation system	*Hiero*
Language model data	*160 M words*
Translation model data	*30M words*
Number of partitions	*30*
DEV set for baseline MERT	*MT03*
DEV set for reranking	*MT04*
Test sets	*MT05, MT06*
N-best size	*300 unique*
Training algorithm	*averaged perceptron*

Data Selection: varying T_1

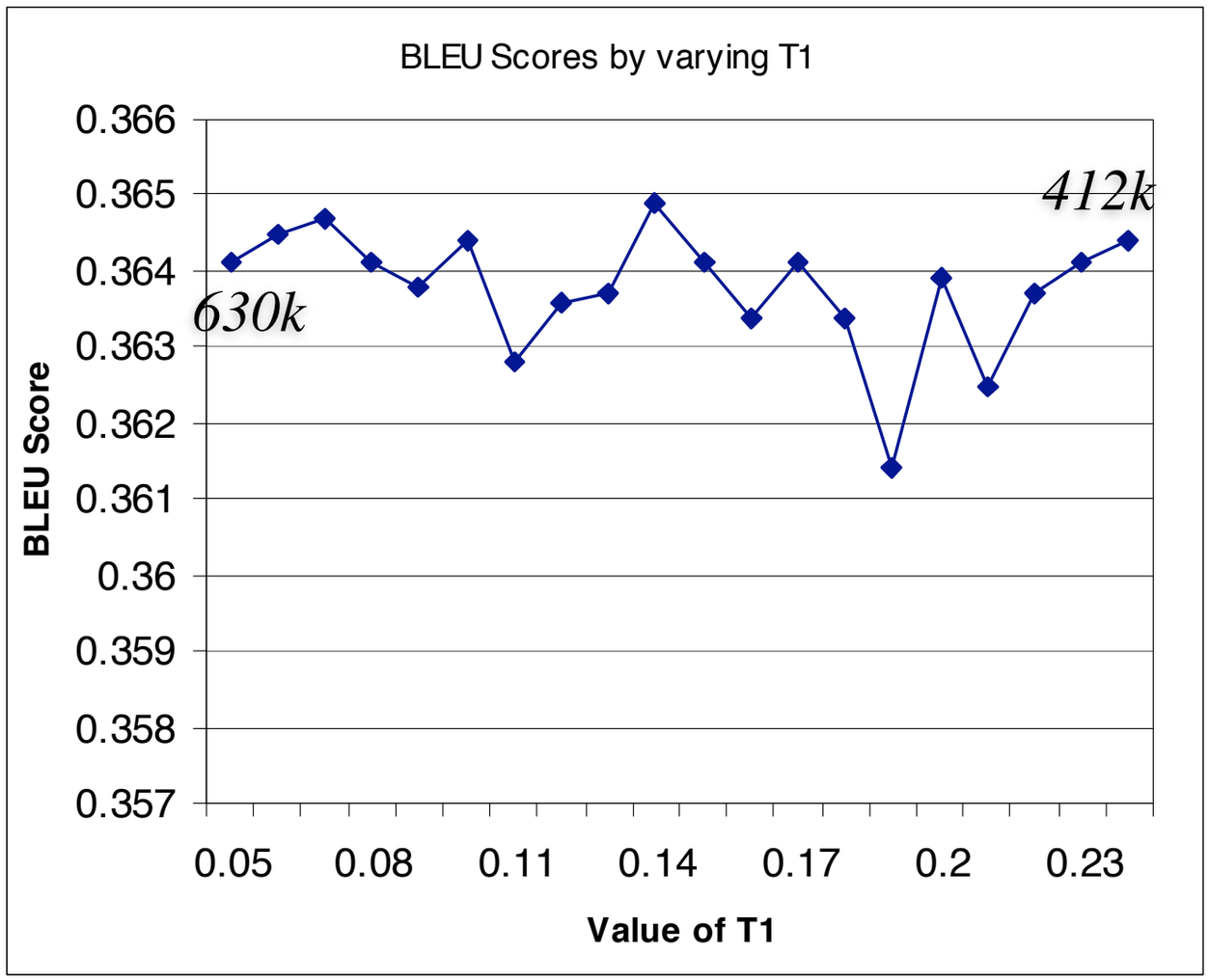

Figure 5: BLEU Scores on MT'04 when varying the value of $T_1 \in [0.05, 0.25]$ with a step size 0.01.

$\mathbf{G(ref, oracle) > T_1}$ → *matched translation*

Data Selection: varying T_2

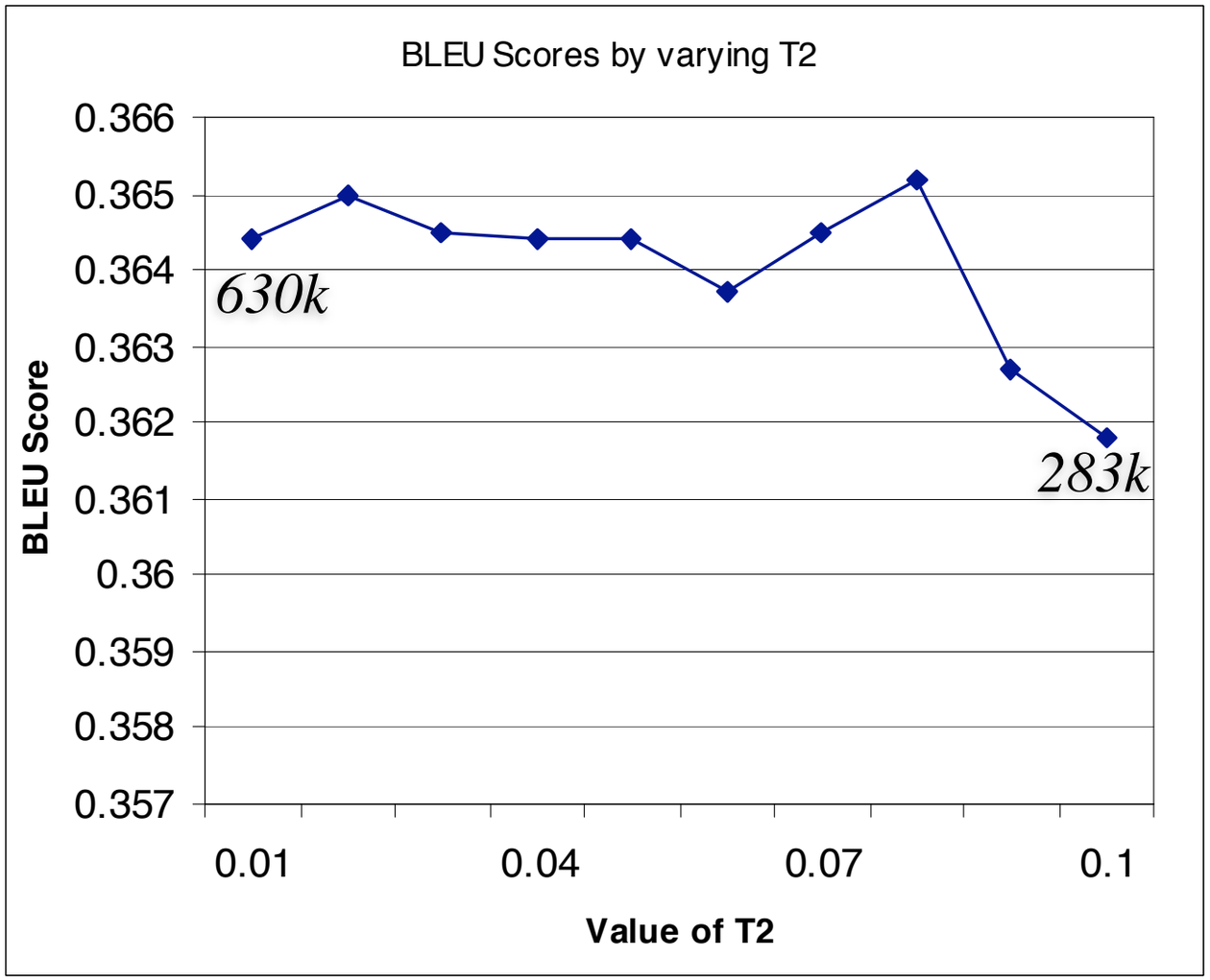

Figure 6: BLEU Scores on MT'04 when varying the value of $T_2 \in [0.01, 0.10]$ with a step size 0.01.

$$\mathbf{G(ref, oracle) - G(ref, 1best) > T_2}$$ → *profitable*

Data Selection: varying T_3

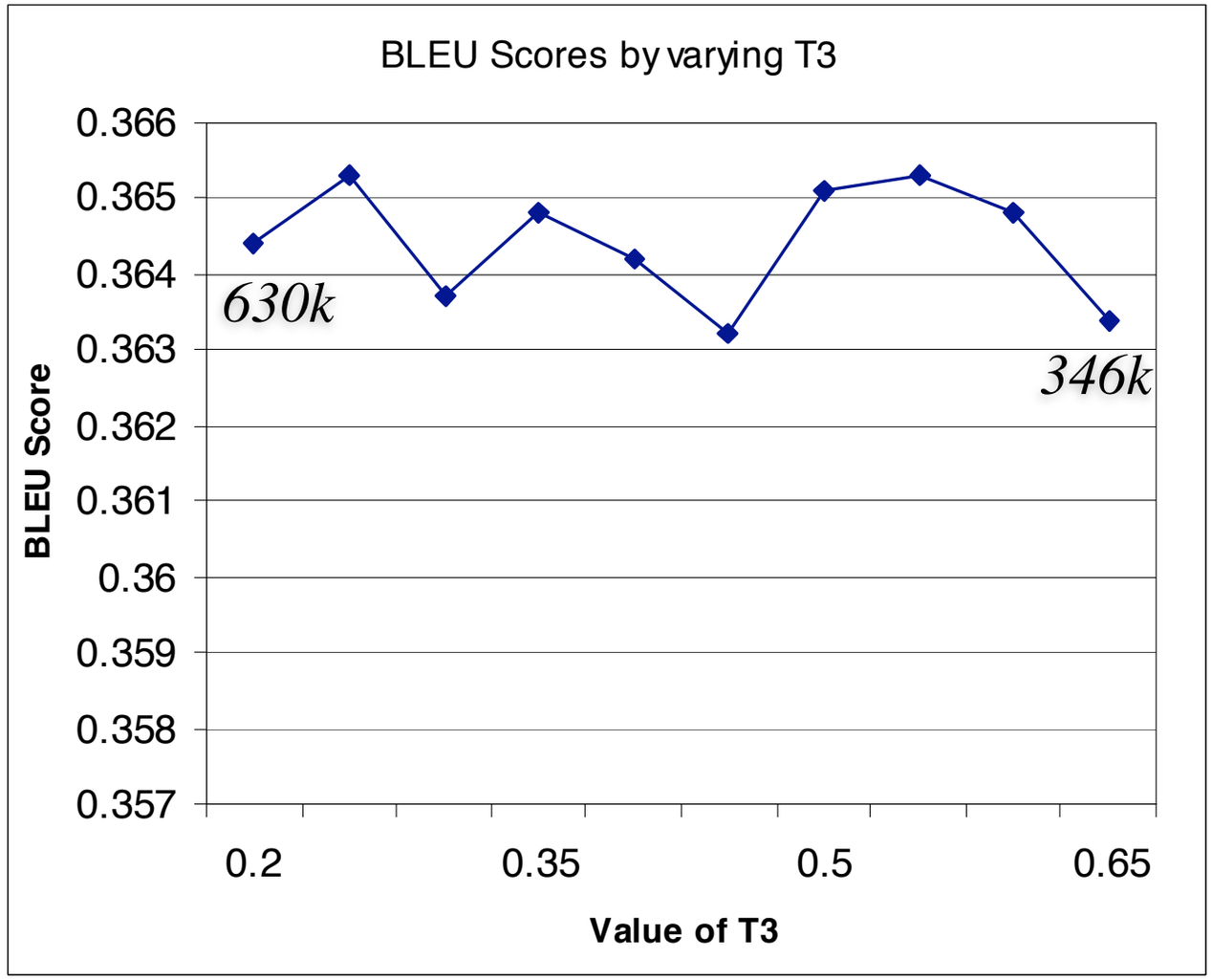

Figure 7: BLEU Scores on MT'04 when varying the value of $T_3 \in [0.20, 0.75]$ with a step size 0.05.

$$\mathbf{G(oracle, 1best) > T_3} \Rightarrow \textit{correctable}$$

Experiments: reranking results

Task	Baseline	Reranking	
		Full	Selected
MT'04	0.357	**0.365**	0.365
MT'05	0.326	0.332	**0.333**
MT'06	0.283	0.292	**0.294**

Experiments: reranking results

Task	Baseline	Reranking	
		Full	Selected
MT'04	0.357	**0.365**	0.365
MT'05	0.326	0.332	**0.333**
MT'06	0.283	0.292	**0.294**

T_1	T_2	T_3	Selected data
0.10	0.01	0.25	610K out of 1M

Experiments: reranking results

Task	Baseline	Reranking	
		Full	Selected
MT'04	0.357	**0.365**	0.365
MT'05	0.326	0.332	**0.333**
MT'06	0.283	0.292	**0.294**

n-gram	active
1-gram	34k
2-gram	1908k

Summary

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- **We have developed a discriminative n-gram LM to rerank MT outputs**

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- We have developed a discriminative n-gram LM to rerank MT outputs
- Discriminative LM reranking improves the translation quality over a state of the art system
- With data selection, we can train a better/comparable model using less data

Hypergraph-based Discriminative Rescoring

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- generate a hypergraph (instead of an n-best) for each Chinese sentence
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- the hypergraph is pruned using the posterior pruning

Hypergraph rescoring results

System		MT04	MT05	MT06
Baseline	Chiang'07	34.6	31.8	NA
	Ours	35.7	32.6	28.3
N-best		**36.5**	**33.3**	**29.4**
Hypergraph		35.9	33.0	28.2

Joshua: an open-source parsing-based MT decoder

- Team members
  - **JHU**: Zhifei Li, Chris Callison-Burch, Sanjeev Khudanpur, Wren Thornton, Jonathan Weese, and Omar Zaidan
  - **UMD**: Chris Dyer
  - **U of Minnesota**: Lane Schwartz
- Functions
  - Chart-parsing, pruning, language model integration, kbest extraction, distributed and parallel decoding
  - Suffix-array based grammar extraction
  - Minimum error rate training

Thank you!
谢谢!