Automatic End-to-End Data Integration using Large Language Models

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Motivation

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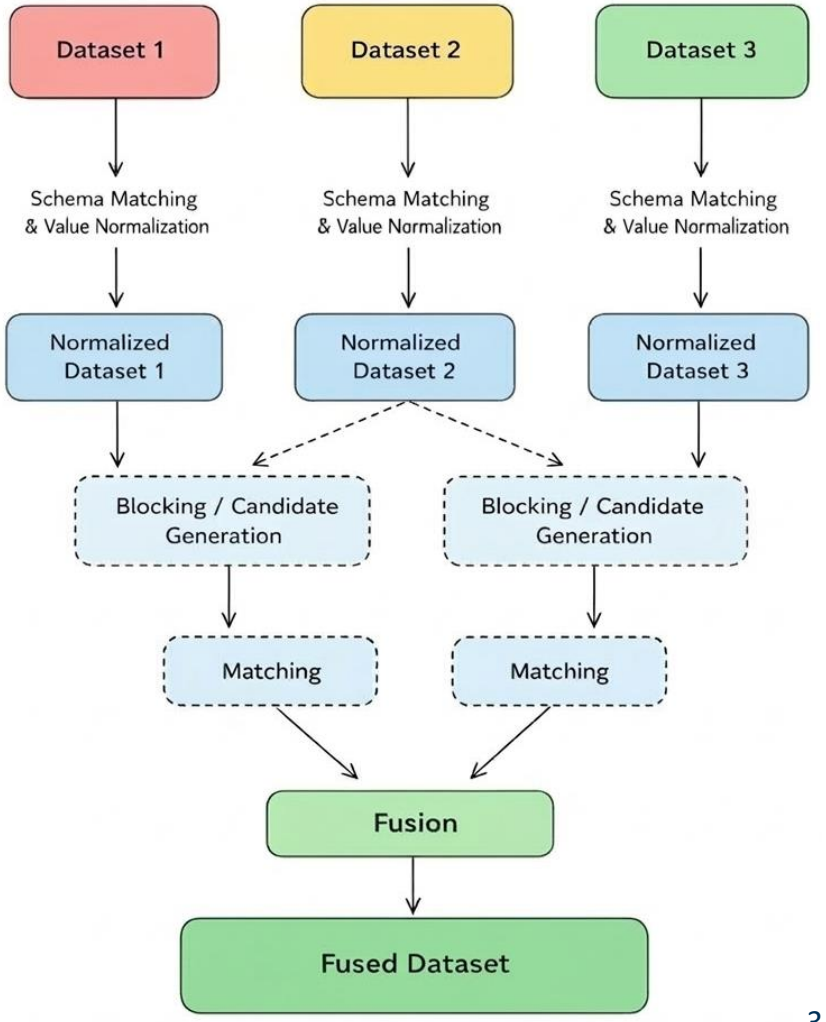
- **Data integration:** combines data from multiple heterogeneous sources into a unified dataset
- Each integration step traditionally requires substantial manual effort from data engineers

→ **Research Question: Can LLMs replace human involvement in configuring end-to-end data integration pipelines?**



Human versus Automatic Data Integration Pipeline

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- **For each use case, we compare a human silver-standard pipeline with a fully automatic LLM-based pipeline**
- Both pipelines use the same core library: **PyDI**
- The automatic system configures the pipeline fully autonomously
- We then compare end-to-end results on three case studies

→ **Difference = who creates the configuration, trainings and validation data**

Case Studies

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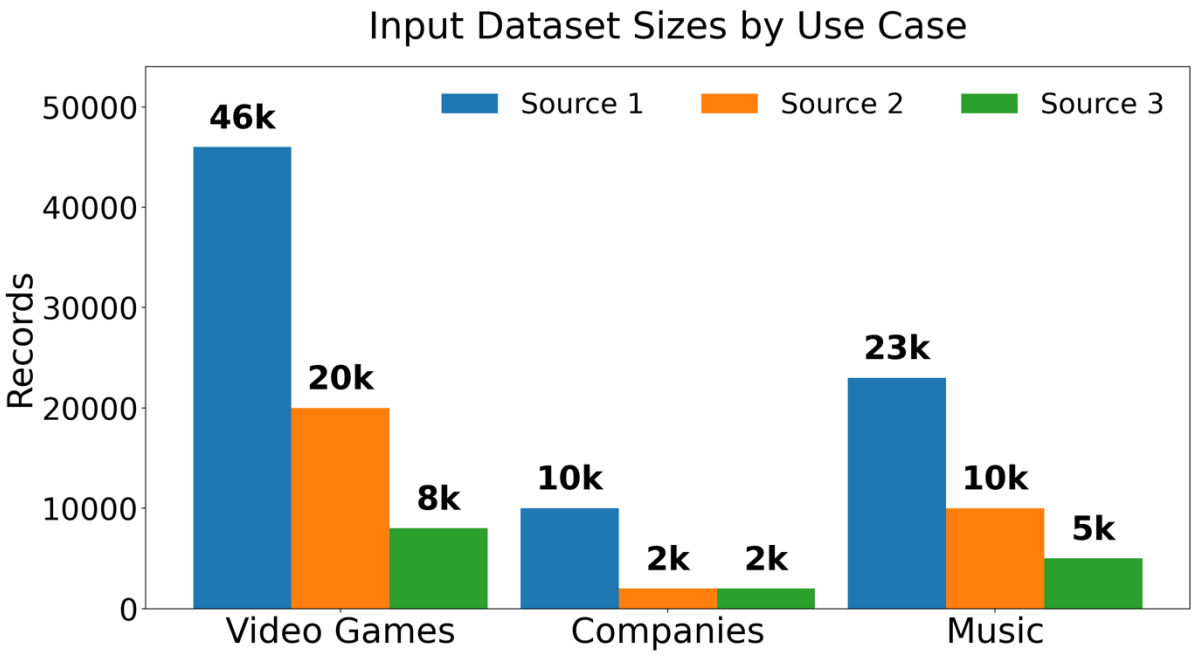
- **Three case studies, each integrating 3 heterogeneous datasets:**
- **Video Games:** Challenges are matching games across platforms, multiple taxonomies (platform etc.)
- **Companies:** Challenges are name variations (abbreviations, legal suffixes), financial scale normalization
- **Music:** Challenges are duration format normalization, varying country naming conventions



Example: Schema Heterogeneity

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- Source attributes differ in naming, coverage, and semantics
- Some attributes have generic names like Attribute_x and can only be matched using the values
- Target schemas are provided by the usecases

Case Study	Source	Rows	Attrs	Density	Attributes
Music	Discogs	22,627	8	98.4%	rec_uid, title_str, performer, pub_dt, origin_loc, imprint, category, tracks_track-name
	Last.fm	9,865	5	78.7%	item_code, album_title, band, tracks_track-name, album_length_min
	MusicBrainz	4,763	7	83.3%	Attribute_1, Attribute_2, Attribute_3, Attribute_4, Attribute_5, Attribute_6, Attribute_7
	Target Schema	–	8	–	id, name, artist, release-date, release-country, label, genre, tracks, duration

Schema Matching

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- **Schema matching = map source columns to target attributes**
- Humans: inspect column names and sample values, then write mappings manually
- Automatic pipeline: uses column names, value summaries, sample rows
- Both use a target schema

→ **Same result: 67/67 correspondences, F1 = 1.00**

Benchmark	Human	LLM	Label	Instance
Games	**1.00**	**1.00**	0.23	0.00
Companies	**1.00**	**1.00**	0.35	0.32
Music	**1.00**	**1.00**	0.38	0.24
Average	**1.00**	**1.00**	0.32	0.19

Value Normalization

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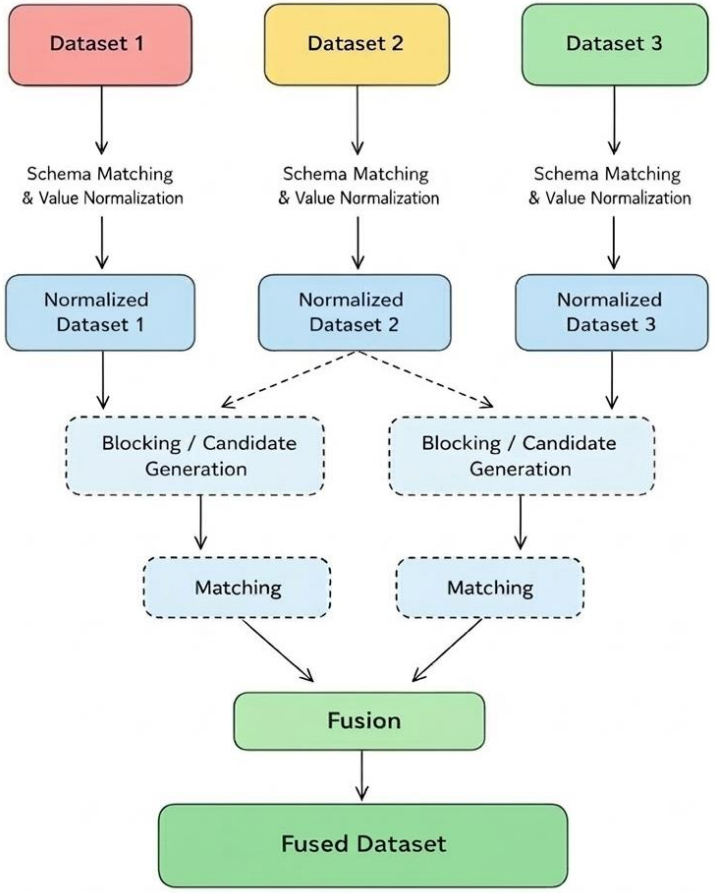
- Humans: custom normalization functions and simple value mappings
- **Automatic pipeline:**
- Automatic column profiling selects code normalizers
- Maps values to target taxonomies

→ **Automatic pipeline normalizes more categorical and taxonomy values than humans**

Games Examples

Type	Raw value	Human	LLM
Taxonomy	PS4	PlayStation 4	PlayStation 4
Taxonomy	NES	NES	Nintendo Entertain-ment System
Date	11/15/2013	2013-11-15	2013-11-15

Recap - Where Are We?



Entity Matching: LLM Training Data

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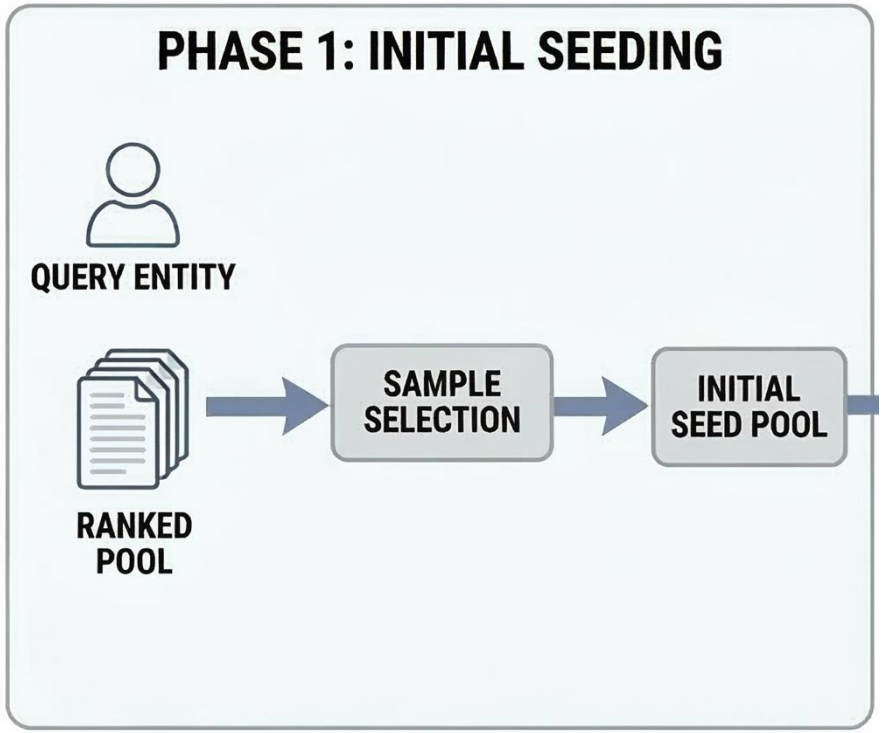
- Humans hand-annotate pairs for training classifiers
- **Active learning workflow with LLM as labeler**
- Step 1 - Seeding label pairs
  - Yields ~100 (30/70) labeled seed pairs per dataset pair



Entity Matching: LLM Training Data

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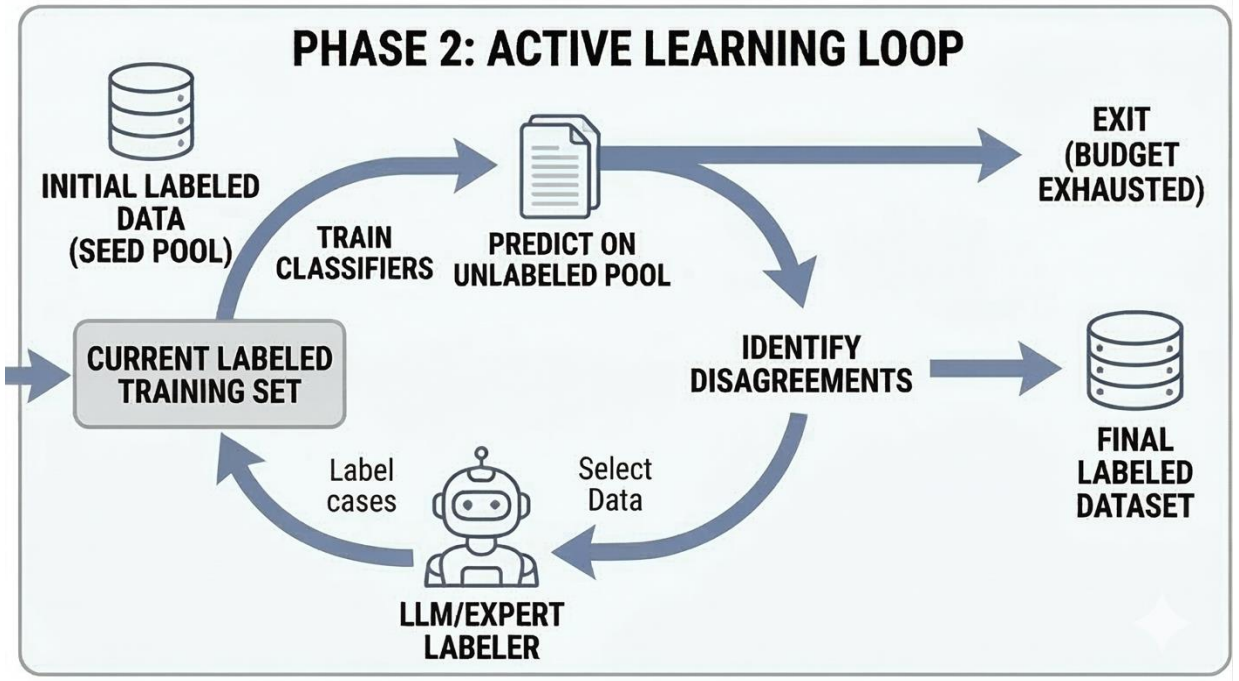
- **Active learning workflow with LLM as labeler**
- **Step 2 - Active learning loop:**
  - Train 5 classifiers, select 100 pairs with highest prediction disagreement
  - GPT-5.2 labels disputed pairs → retrain → repeat until budget exhausted
  - Training set augmented with 20% random samples to counter selection bias



Entity Matching: Results

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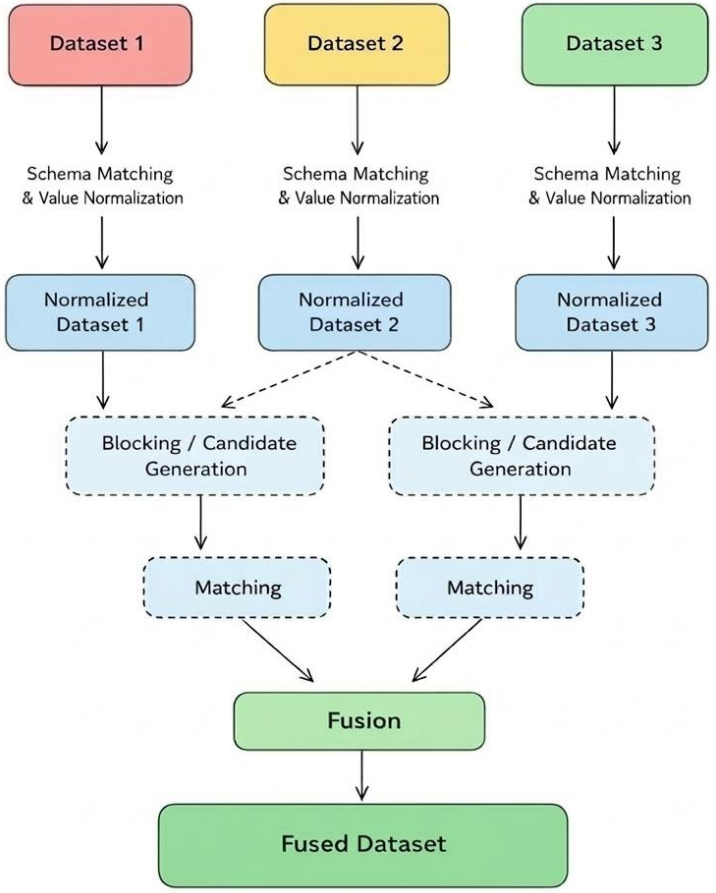
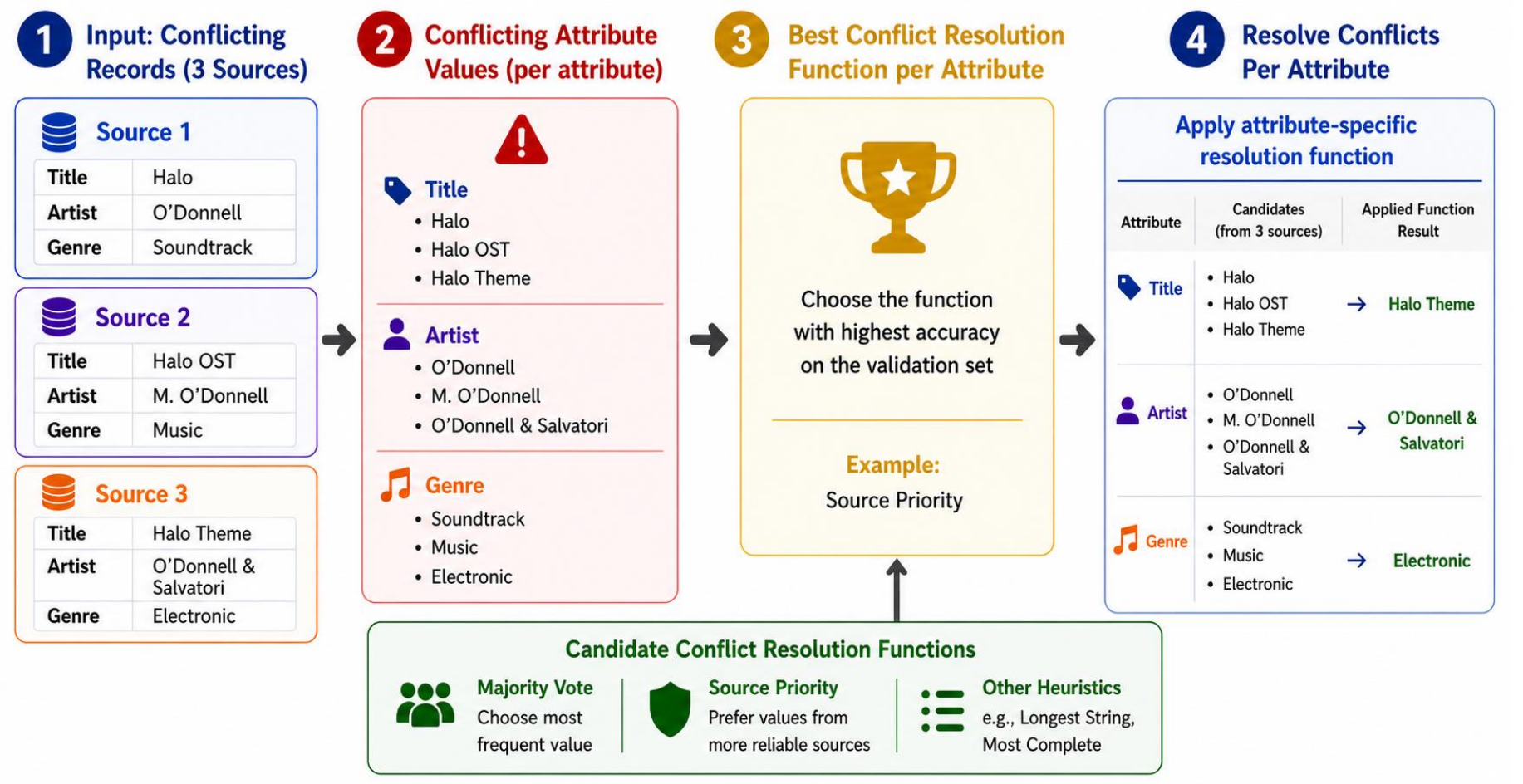
Dataset Pair	Human Config	Human Labels	LLM Labels
Games: DBp - Meta	**0.93**	0.83	0.85
Games: DBp - Sales	0.93	0.84	**0.98**
Comp: DBp - Forbes	0.86	**0.95**	0.94
Comp: Forbes - FC	0.87	**0.90**	**0.90**
Music: Disc - MB	0.80	**0.99**	**0.99**
Music: Last - MB	0.98	**0.99**	0.97
Average	0.89	0.92	**0.94**

→ **LLM Labels achieve 0.94 avg F1 (best)**

Recap - Where Are We?



Data Fusion


1 Input: Conflicting Records (3 Sources)
Source 1
Title Halo
Artist O'Donnell
Genre Soundtrack
Source 2
Title Halo OST
Artist M. O'Donnell
Genre Music
Source 3
Title Halo Theme
Artist O'Donnell & Salvatori
Genre Electronic
2 Conflicting Attribute Values (per attribute)
Title
• Halo
• Halo OST
• Halo Theme
Artist
• O'Donnell
• M. O'Donnell
• O'Donnell & Salvatori
Genre
• Soundtrack
• Music
• Electronic
3 Best Conflict Resolution Function per Attribute
Choose the function with highest accuracy on the validation set
Example:
Source Priority
4 Resolve Conflicts Per Attribute
Apply attribute-specific resolution function
Attribute
Candidates (from 3 sources)
Applied Function Result
Title
• Halo
• Halo OST
• Halo Theme
→ Halo Theme
Artist
• O'Donnell
• M. O'Donnell
• O'Donnell & Salvatori
→ O'Donnell & Salvatori
Genre
• Soundtrack
• Music
• Electronic
→ Electronic
Candidate Conflict Resolution Functions
Majority Vote
Choose most frequent value
Source Priority
Prefer values from more reliable sources
Other Heuristics
e.g., Longest String, Most Complete

Fusion Validation Data Creation

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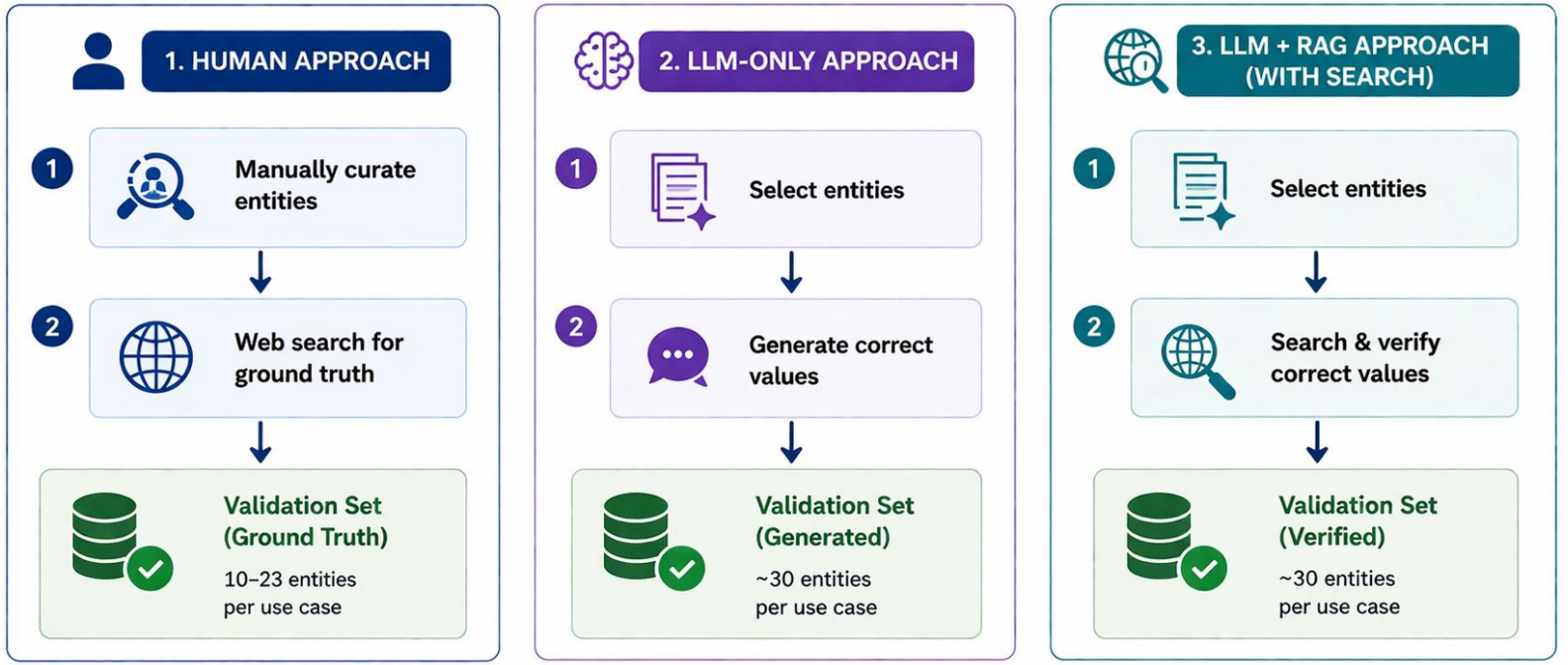
Goal: generate validation sets to select the best conflict resolution methods functions per attribute



Data Fusion

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- **Data fusion = choose the correct value when sources disagree**
- Humans & automatic pipeline use the validation set to iteratively find the best fusion heuristic

→ **Best result still comes from human validation; the gap is mainly Companies because values are time-sensitive**

Benchmark	Human Config	Human Val.	LLM Val.	LLM + RAG
Games	0.83	**0.87**	**0.87**	**0.87**
Companies	0.80	**0.86**	0.71	0.74
Music	**0.77**	0.72	0.71	0.71
Average	**0.80**	**0.82**	0.76	0.77

Runtime and Cost Analysis

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LLM API costs per use case; Config: ~1.9h (LLM) vs. ≥19h (human)

Pipeline Step	Games	Companies	Music	Total
Schema Matching	$0.02	$0.02	$0.02	$0.06
Normalization	$0.13	$0.36	$0.17	$0.66
Training Set Gen.	$1.33	$1.96	$1.66	$4.95
Fusion Val. (LLM)	$0.22	$0.15	$0.23	$0.60
Fusion Val. (RAG)	$7.46	$6.07	$7.45	$20.98
Total per Case	**$9.16**	**$8.56**	**$9.53**	**$27.25**

→ **10× reduction in configuration effort at ~$9 per use case**

Conclusion

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- **LLM pipeline produced outcomes close to or surpassing humans**
  - Strength of LLM pipeline: schema matching, value normalization, and entity-matching labels
  - Main weakness: data fusion on time-sensitive attributes
- **10x runtime reduction: ~1.9h versus ≥19 human hours per use case**
- **9 USD per use case**

Future Work

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- **Agent-based refinement:** agentic architecture feeding downstream results back to earlier steps
- **Human-agent collaboration:** pipeline outputs as starting point for collaborative refinement
- **Dynamic code generation:** LLM-based coding agents for transformation functions

Thank you for listening

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Paper

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