



# Structured Extraction from Catering Offer Emails

Automating the extraction of key offer details from unstructured email text using NLP techniques



## The Challenge

# Manual Offer Comparison Creates Bottlenecks

### Current Reality

- Event organizers send RFPs to multiple catering suppliers
- Offers arrive as free form emails with varying formats
- Manual extraction into spreadsheets is time consuming and error-prone
- Critical details may be missed or misinterpreted

### Key Challenges

- **Unstructured text:** Different writing styles across suppliers
- **Format variability:** Prices, dates, policies appear in different places
- **Missing information:** Fields may be implicit or omitted entirely
- **Inconsistent units:** "around 200 per person", "+VAT", ranges

# Project Overview: Email-to-JSON Extraction

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```



## Input

Raw catering offer email (subject + body) in natural English



## Processing

NLP model extracts structured fields using LLM or fine tuned approach



## Output

Standardized JSON with supplier name, pricing, guests, VAT, kosher level, bar, dates, policies



**Novel Contribution:** We propose a new synthetic dataset and a systematic evaluation

# Model Pipeline & Synthetic Data Generation

01

## Generate Ground Truth JSON

Sample realistic values: prices, guest counts, VAT status, kosher options, bar inclusion, dates, cancellation policies

02

## Create Synthetic Emails

LLM generates business style English emails from JSON templates with natural variation and noise

03

## Train & Evaluate Models

Compare zero shot LLM, few shot LLM with examples, and fine tuned smaller open-source models

04

## Validate Predictions

Compare predicted JSON against ground truth, compute field wise and JSON level accuracy metrics

### Zero Shot Baseline

Schema description only

### Few Shot Baseline

Schema + example pairs

### Fine Tuned Model

Supervised on synthetic dataset

# Metrics and KPIs

How would you measure the results?

## Extraction Quality

- Field wise performance on key numeric, boolean, and categorical fields
- "All key fields correct" accuracy per email (JSON level accuracy)

## Data Generation Quality

- Spot check a sample of generated emails to ensure they are realistic and consistent with their JSON

## Comparison Protocol

- Compare the model's predicted JSON (pred\_json) with the ground truth JSON (gold\_json) for each email
- Compute metrics per field and overall

## Boolean / Categorical Fields

- Examples: includes\_vat, is\_kosher, includes\_bar, price\_type
- Metric: Accuracy (and optionally F1)

## Numeric Fields

- Examples: price\_value, min\_guests, max\_guests
- Metrics: Exact match accuracy; optionally MAE (mean absolute error)

## Short Text Fields

- Examples: kosher\_supervision, date\_available
- Metric: Exact match after simple normalization

📌 **Key Success Metric:** "Key-fields JSON accuracy" - percentage of emails where all core fields (price, VAT, kosher, min guests, bar) are predicted correctly. Ground truth comes directly from the original JSON used to generate each synthetic email.