CENG 442 - Natural Language Processing

Assignment 1: Azerbaijani Text Preprocessing + Word Embeddings (Domain-Aware)

Deadline: 31.10.2025 23:45 | Group size: up to 4 students

Overview

Goal: Clean five Azerbaijani text datasets for sentiment analysis; keep all three polarities as numeric values (Negative=0.0, Neutral=0.5, Positive=1.0). Produce a simple two-column Excel per dataset. Train Word2Vec and FastText on the cleaned text. Make the pipeline lightly domain-aware (news/social/reviews/general). Keep it simple and reproducible.

1) Deliverables (what to submit)

- Five Excel files (one per dataset) with two columns: cleaned_text (string), sentiment_value (float in {0.0, 0.5, 1.0}).
- One plain-text file corpus_all.txt: all cleaned text as one sentence per line, lowercase, punctuation-free. Prepend a simple domain tag token (e.g., domnews, domsocial, domreviews, domgeneral) to each line.
- Two embedding models trained on the combined corpus: embeddings/word2vec.model and embeddings/fasttext.model.
- A short report as README.md in your GitHub repository (see Section 9).

2) Datasets & Label Mapping

Canonical file names and columns (adapt if your local names differ):

- labeled-sentiment.xlsx 3-class (columns: text, sentiment)
- test_1_xlsx binary (columns: text, label)
- train_3_xlsx binary (columns: text, label)
- train-00000-of-00001.xlsx 3-class (columns: text, labels)
- merged_dataset_CSV_1_xlsx binary (columns: text, labels; drop Unnamed: 0 if present)

Sentiment mapping to sentiment_value: Negative $\rightarrow 0.0$, Neutral $\rightarrow 0.5$, Positive $\rightarrow 1.0$.

3) Technologies (what & why)

- Python 3: Main scripting environment.
- pandas: Excel I/O and vectorized preprocessing.
- regex (re): Find/replace for URLs, emails, mentions, numbers, hashtags.

- unicodedata: Azerbaijani-aware casing $(\dot{l} \rightarrow i, l \rightarrow i)$ and Unicode normalization.
- ftfy (optional): Fix common encoding glitches.
- gensim: Train Word2Vec and FastText embeddings.
- openpyxl: Excel engine for .xlsx I/O.

Install essentials:

```
pip install pandas gensim openpyxl regex ftfy scikit-learn
```

4) Simple Cleaning Rules (Azerbaijani-aware)

- Lowercase with Azerbaijani rules (replace $\dot{I} \rightarrow i$, $I \rightarrow i$ before lower()).
- Replace URLs→URL, emails→EMAIL, phone numbers→PHONE, @mentions→USER.
- Strip HTML tags/entities; drop # but keep hashtag text (split camelCase hashtags).
- Collapse ≥3 repeated letters to 2 (cooool→coool).
- Replace digits with < NUM > (be consistent).
- Remove standalone punctuation and extra spaces; keep letters: ə, ĕ, ı, ö, ü, ç, ş (plus x, q).
- Remove single-letter tokens except o, e.
- Drop exact duplicates and empty rows.

5) Mini Challenges (easy, programming practice)

- Hashtag split: #QarabagIsBack → 'qarabag is back'.
- Emoji mapping: build a tiny dict to map emojis to EMO_POS/EMO_NEG before tokenization.
- Stopword research: compare Azerbaijani with at least one other language (TR/EN/RU), propose 10 candidates (do not remove negations like yox, deyil, heç).
- Negation scope (toggle): mark next 3 tokens with _NEG after a negator (yox, deyil, heç, qətiyyən, yoxdur) and compare nearest neighbors qualitatively.
- Simple deasciify: apply small map (cox→çox, yaxsi→yaxşı) and report how many tokens changed.

6) Domain-Aware Additions (simple & useful)

Use a tiny 4-class domain scheme: news, social, reviews, general. Detect with simple rules; apply a small domain-specific normalization; and tag lines in corpus_all.txt.

```
# --- Domain detection --- import re
```

```
NEWS HINTS = re.compile(r"\b(apa|trend|azertac|reuters|bloomberg|dha|aa)\b", re.I)
REV HINTS = re.compile(r"\b(azn|manat|qiym\thetat|aldım|ulduz|çox yaxşı|çox pis)\b",
re.I)
def detect domain(text: str) -> str:
   s = text.lower()
   if NEWS HINTS.search(s): return "news"
   if SOCIAL_HINTS.search(s): return "social"
   if REV HINTS.search(s): return "reviews"
   return "general"
# --- Domain-specific normalization (reviews) ---
PRICE RE = re.compile(r"\b\d+\s*(azn|manat)\b", re.I)
STARS RE = re.compile(r"\b([1-5])\s*ulduz\b", re.I)
POS RATE = re.compile(r"\bçox yaxşı\b")
NEG RATE = re.compile(r"\bçox pis\b")
def domain specific normalize(cleaned: str, domain: str) -> str:
   if domain == "reviews":
       s = PRICE RE.sub(" <PRICE> ", cleaned)
       s = STARS RE.sub(lambda m: f" <STARS {m.group(1)}> ", cleaned)
       s = POS RATE.sub(" <RATING POS> ", s)
       s = NEG RATE.sub(" <RATING NEG> ", s)
       return " ".join(s.split())
    return cleaned
# --- Domain tag token for corpus (no punctuation) ---
def add_domain_tag(line: str, domain: str) -> str:
   return f"dom{domain} " + line # e.g., 'domnews', 'domreviews'
```

7) Pipeline Code (two-column outputs + domain-tagged corpus)

```
# -*- coding: utf-8 -*-
import re, html, unicodedata
import pandas as pd
from pathlib import Path
   from ftfy import fix text
except Exception:
   def fix text(s): return s
# Azerbaijani-aware lowercase
def lower az(s: str) -> str:
   if not isinstance(s, str): return ""
   s = unicodedata.normalize("NFC", s)
    s = s.replace("I", "1").replace("İ", "i")
    s = s.lower().replace("i","i")
    return s
HTML TAG RE = re.compile(r'' < [^>] +>")
URL_RE = re.compile(r"(https?://\S+|www\.\S+)", re.IGNORECASE)
EMAIL RE = re.compile(r"\b[\w\.-]+@[\w\.-]+\.\w+\b", re.IGNORECASE)
PHONE\_RE = re.compile(r"\+?\d[\d\-\s\(\)]{6,}\d")
USER RE = re.compile(r''@\w+")
MULTI_PUNCT = re.compile(r"([!?.,;:])\1{1,}")
MULTI SPACE = re.compile(r"\s+")
REPEAT CHARS= re.compile(r"(.)\1{2,}", flags=re.UNICODE)
TOKEN RE = re.compile(
```

```
r"[A-Za-zəəĞğIıİiÖÖÜüÇ窺XxQq]+(?:'[A-Za-zəəĞğIıİiÖÖÜüÇ窺XxQq]+)?"
       r"|<NUM>|URL|EMAIL|PHONE|USER|EMO (?:POS|NEG)"
)
EMO MAP = {"♥":"EMO POS","♥":"EMO POS","♥":"EMO POS","♥":"EMO POS"," → ":"EMO                     SLANG MAP = {"slm":"salam","tmm":"tamam","sagol":"sağol","cox":"çox","yaxsi":"yaxşı"}
NEGATORS = {"yox", "deyil", "heç", "q@tiyy@n", "yoxdur"}
# Domain helpers (paste from Section 6)
import re
NEWS HINTS
                      = re.compile(r"\b(apa|trend|azertac|reuters|bloomberg|dha|aa)\b", re.I)
REV HINTS
                    = re.compile(r"\b(azn|manat|qiym9t|aldım|ulduz|çox yaxşı|çox pis)\b",
re.I)
PRICE RE
                       = re.compile(r"\b\d+\s*(azn|manat)\b", re.I)
STARS RE
                      = re.compile(r"\b([1-5])\s*ulduz\b", re.I)
POS RATE
                      = re.compile(r"\bçox yaxşı\b")
NEG RATE
                      = re.compile(r"\bçox pis\b")
def detect domain(text: str) -> str:
       s = text.lower()
       if NEWS HINTS.search(s): return "news"
       if SOCIAL HINTS.search(s): return "social"
       if REV HINTS.search(s): return "reviews"
       return "general"
def domain_specific_normalize(cleaned: str, domain: str) -> str:
       if domain == "reviews":
              s = PRICE RE.sub(" <PRICE> ", cleaned)
              s = STARS RE.sub(lambda m: f" <STARS_{m.group(1)}> ", cleaned)
              s = POS RATE.sub(" <RATING POS> ", s)
              s = NEG RATE.sub(" < RATING NEG> ", s)
              return " ".join(s.split())
       return cleaned
def add domain tag(line: str, domain: str) -> str:
       return f"dom{domain} " + line # no punctuation
def normalize text az(s: str, numbers to token=True, keep sentence punct=False) -> str:
       if not isinstance(s, str): return ""
       # emoji map first
       for emo, tag in EMO MAP.items():
             s = s.replace(emo, f" {tag} ")
       s = fix_text(s)
       s = html.unescape(s)
       s = HTML_TAG_RE.sub(" ", s)
       s = URL RE.sub(" URL ", s)
       s = EMAIL RE.sub(" EMAIL ", s)
       s = PHONE RE.sub(" PHONE ", s)
       # Hashtag: keep text, split camelCase
       s = re.sub(r"#([A-Za-z0-9]+)", lambda m: " " + re.sub('([a-z])([A-Z])', r'\1 \2',
m.group(1)) + " ", s)
       s = USER RE.sub(" USER ", s)
       s = lower az(s)
       s = MULTI PUNCT.sub(r"\1", s)
       if numbers to token:
              s = re.sub(r"\d+", " < NUM> ", s)
       if keep sentence punct:
              s = re.sub(r"[^\w\s<>'ðďiösüçðĞIİÖSÜÇxqXQ.!?]", " ", s)
       else:
```

```
s = re.sub(r"[^\w\s<>'ðğiöşüçðĞİİÖŞÜÇxqXQ]", " ", s)
    s = MULTI SPACE.sub(" ", s).strip()
   toks = TOKEN RE.findall(s)
   norm = []
   mark neg = 0
   for t in toks:
        t = REPEAT CHARS.sub(r"\1\1", t)
        t = SLANG_MAP.get(t, t)
        if t in NEGATORS:
            norm.append(t); mark_neg = 3; continue
        if mark neg > 0 and t not in {"URL", "EMAIL", "PHONE", "USER"}:
           norm.append(t + "_NEG"); mark_neg -= 1
        else:
           norm.append(t)
    norm = [t for t in norm if not (len(t) == 1 and t not in {"o", "e"})]
    return " ".join(norm).strip()
def map sentiment value(v, scheme: str):
    if scheme == "binary":
        try: return 1.0 if int(v) == 1 else 0.0
        except Exception: return None
    s = str(v).strip().lower()
    if s in {"pos", "positive", "1", "müsb@t", "good", "pozitiv"}: return 1.0
    if s in {"neu", "neutral", "2", "neytral"}: return 0.5
    if s in {"neg", "negative", "0", "mənfi", "bad", "negativ"}: return 0.0
    return None
def process_file(in_path, text_col, label_col, scheme, out_two_col_path,
remove stopwords=False):
    df = pd.read excel(in path)
    for c in ["Unnamed: 0", "index"]:
       if c in df.columns: df = df.drop(columns=[c])
    assert text col in df.columns and label col in df.columns, f"Missing columns in
{in path}"
    # original text kept for domain detection
    df = df.dropna(subset=[text col])
    df = df[df[text col].astype(str).str.strip().str.len() > 0]
    df = df.drop duplicates(subset=[text col])
    # base clean
    \texttt{df["cleaned text"] = df[text col].astype(str).apply(lambda s: normalize text az(s))}
    # domain-aware tweak
    df[" domain "] = df[text_col].astype(str).apply(detect_domain)
    df["cleaned text"] = df.apply(lambda r:
domain_specific_normalize(r["cleaned_text"], r["__domain__"]), axis=1)
    # optional stopwords (kept minimal, sentiment words preserved)
    if remove_stopwords:
        sw =
set(["və","ilə","amma","ancaq","lakin","ya","həm","ki","bu","bir","o","biz","siz","mən"
,"sən","orada","burada","bütün","hər","artıq","çox","az","ən","də","da","üçün"])
        for keep in ["deyil", "yox", "heç", "qətiyyən", "yoxdur"]:
            sw.discard(keep)
        df["cleaned text"] = df["cleaned text"].apply(lambda s: " ".join([t for t in
s.split() if t not in sw]))
    # sentiment mapping (0.0 / 0.5 / 1.0)
    df["sentiment value"] = df[label col].apply(lambda v: map sentiment value(v,
scheme))
    df = df.dropna(subset=["sentiment value"])
    df["sentiment value"] = df["sentiment value"].astype(float)
```

```
# final two-column output
   out df = df[["cleaned text", "sentiment value"]].reset index(drop=True)
   Path(out two col path).parent.mkdir(parents=True, exist ok=True)
   out df.to excel(out two col path, index=False)
   print(f"Saved: {out two col path} (rows={len(out df)})")
def build corpus txt(input files, text cols, out txt="corpus all.txt"):
    """Create domain-tagged, lowercase, punctuation-free corpus (one sentence per
line)."""
   lines = []
   for (f, text_col) in zip(input_files, text_cols):
       df = pd.read_excel(f)
       for raw in df[text col].dropna().astype(str):
           dom = detect domain(raw)
           s = normalize text az(raw, keep sentence punct=True)
           parts = re.split(r"[.!?]+", s)
           for p in parts:
               p = p.strip()
               if not p: continue
               p = re.sub(r"[^\w\shape]^{\w\shape})", "", p) # remove punctuation
               p = " ".join(p.split()).lower()
                   lines.append(f"dom{dom} " + p)
   with open(out txt, "w", encoding="utf-8") as w:
       for ln in lines:
           w.write(ln + "\n")
   print(f"Wrote {out_txt} with {len(lines)} lines")
if __name__ == "__main__":
   CFG = [
       ("labeled-sentiment.xlsx",
                                        "text", "sentiment", "tri"),
                                        "text", "label", "binary"),
       ("test__1_.xlsx",
       ("train 3 .xlsx",
                                        "text", "label",
                                                             "binary"),
       ("train-00000-of-00001.xlsx", "text", "labels",
                                                            "tri"),
       ("merged_dataset_CSV__1_.xlsx", "text", "labels", "binary"),
   ]
    # two-column outputs
   for fname, tcol, lcol, scheme in CFG:
       out = f"{Path(fname).stem} 2col.xlsx"
       process file(fname, tcol, lcol, scheme, out, remove stopwords=False)
    # combined domain-tagged, punctuation-free corpus
   build corpus txt([c[0] for c in CFG], [c[1] for c in CFG],
out txt="corpus all.txt")
```

8) Train Word2Vec & FastText (combined cleaned_text)

```
from gensim.models import Word2Vec, FastText
import pandas as pd
from pathlib import Path

files = [
    "labeled-sentiment_2col.xlsx",
    "test__1__2col.xlsx",
    "train__3__2col.xlsx",
    "train-00000-of-00001_2col.xlsx",
    "merged_dataset_CSV__1__2col.xlsx",
]

sentences = []
for f in files:
    df = pd.read_excel(f, usecols=["cleaned_text"])
```

```
sentences.extend(df["cleaned_text"].astype(str).str.split().tolist())
Path("embeddings").mkdir(exist_ok=True)
w2v = Word2Vec(sentences=sentences, vector_size=300, window=5, min_count=3, sg=1, negative=10, epochs=10)
w2v.save("embeddings/word2vec.model")
ft = FastText(sentences=sentences, vector_size=300, window=5, min_count=3, sg=1, min_n=3, max_n=6, epochs=10)
ft.save("embeddings/fasttext.model")
print("Saved embeddings.")
```

9) Compare Word2Vec vs FastText (simple metrics)

Evaluate coverage, synonym/antonym similarity and nearest neighbors; report per domain if possible.

```
import pandas as pd
from gensim.models import Word2Vec, FastText
import re
w2v = Word2Vec.load("embeddings/word2vec.model")
ft = FastText.load("embeddings/fasttext.model")
seed words =
["yaxşı","pis","cox","bahalı","ucuz","mükəmməl","dəhşət","<PRICE>","<RATING POS>"]
syn pairs = [("yaxşı","@la"), ("bahalı","qiym@tli"), ("ucuz","s@rf@li")]
ant pairs = [("yaxşı", "pis"), ("bahalı", "ucuz")]
def lexical coverage (model, tokens):
    vocab = model.wv.key to index
    return sum(1 for t in tokens if t in vocab) / max(1,len(tokens))
files = [
    "labeled-sentiment 2col.xlsx",
    "test 1__2col.xlsx",
    "train__3__2col.xlsx",
    "train-00000-of-00001_2col.xlsx",
    "merged dataset CSV 1 2col.xlsx",
]
def read tokens(f):
    df = pd.read excel(f, usecols=["cleaned text"])
    return [t for row in df["cleaned text"].astype(str) for t in row.split()]
print("== Lexical coverage (per dataset) ==")
for f in files:
    toks = read tokens(f)
    cov w2v = lexical coverage(w2v, toks)
    cov ftv = lexical coverage(ft, toks) # FT still embeds OOV via subwords
   print(f"{f}: W2V={cov w2v:.3f}, FT(vocab)={cov ftv:.3f}")
from numpy import dot
from numpy.linalg import norm
def cos(a,b): return float(dot(a,b)/(norm(a)*norm(b)))
def pair sim (model, pairs):
   vals = []
    for a,b in pairs:
        try: vals.append(model.wv.similarity(a,b))
```

```
except KeyError: pass
             return sum(vals)/len(vals) if vals else float('nan')
syn w2v = pair sim(w2v, syn pairs)
syn ft = pair sim(ft, syn pairs)
ant_w2v = pair_sim(w2v, ant pairs)
ant ft = pair sim(ft, ant pairs)
print("\n== Similarity (higher better for synonyms; lower better for antonyms) ==")
print(f"Synonyms: W2V={syn_w2v:.3f}, FT={syn_ft:.3f}")
print(f"Antonyms: W2V={ant_w2v:.3f}, FT={ant_ft:.3f}")
print(f"Separation (Syn - Ant): W2V={(syn w2v - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn ft - ant w2v):.3f}, FT={(syn 
ant ft):.3f}")
def neighbors (model, word, k=5):
             try: return [w for w, in model.wv.most similar(word, topn=k)]
             except KeyError: return []
print("\n== Nearest neighbors (qualitative) ==")
 for w in seed words:
            print(f" W2V NN for '{w}':", neighbors(w2v, w))
             print(f" FT NN for '{w}':", neighbors(ft,
 # (Optional) domain drift if you train domain-specific models separately:
# drift(word, model a, model_b) = 1 - cos(vec_a, vec_b)
```

10) Report (README.md, ≤3 pages)

- 1) Data & Goal (short): datasets, why keep neutral=0.5.
- 2) Preprocessing: rules in 1 paragraph; before→after examples; duplicates/empties removed.
- 3) Mini Challenges: what you implemented and quick observations (1–2 bullets each).
- 4) Domain-Aware: detection rule(s), domain-specific normalization, how you added dom tags to corpus.
- 5) Embeddings: training settings (short table) and results (coverage, Syn/Ant similarities, NN samples; per domain if possible).
- 6) (Optional) Lemmatization: approach/effect if attempted.
- 7) Reproducibility: versions, seeds, machine; how to run.
- 8) Conclusions: which model worked better for your data and why; next steps.

11) Submission (GitHub + AYBUZEM)

All submissions must be via GitHub. AYBUZEM will only receive a text file with your repolink and group info.

• Create a public GitHub repository named: ceng442-assignment1-<groupname>

- Add your code, two-column outputs, corpus_all.txt, and embeddings/ (models). If models are large, provide a download link in the README.
- Your main report must be README.md (Markdown) at the repository root. It should follow Section 10 and render on the repo homepage.
- Ensure all scripts and notebooks are runnable from a clean clone (provide requirements.txt).
- Add group members (max 4) in README and in AYBUZEM text file.

On AYBUZEM, upload ONE text file named: CENG442_Assignment1_Submission.txt with the following content:

```
Repository: https://github.com/<org-or-user>/ceng442-assignment1-<groupname>
Group members:
    <Full Name 1>
    <Full Name 2>
    <Full Name 3>
    <Full Name 4>
```