Stance

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Stance detection

definition

determine whether the writer is in favour or against some statement

from severe question to preference

- death penalty
- abortion
- liberalisation of markets
- gender star (Genderstern)
- compulsory vaccination

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Stance detection: xstance

paper

X-Stance: A Multilingual Multi-Target Dataset for Stance Detection Jannis Vamvas, Rico Sennrich

see: https://arxiv.org/abs/2003.08385

Stance detection: the writer perspective

- although the overall perspective is crucial, a text reveals more about author
- his/her preferences, values
- he/she argues in favour of particular aspects of the question
- problem: quite often the words being used are neutral

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Stance detection: the writer perspective

```
Frage:
Sind Sie für eine vollständige Liberalisierung der Geschäftsöffnungszeiten
(Geschäfte können die Öffnungszeiten nach freiem Ermessen festlegen)?

Are you in favour of complete liberalisation of business hours (stores are
free to determine opening hours as they see fit)?

true class  FAVOR

Antwort:
Es muss jedoch sicher gestellt werden, dass die Beschäftigen einen Ausgleich
erhalten (mehr Lohn oder zusätzliche Stunden für die Kompensation der Nachtarbeit).

However, it must be ensured that employees receive compensation (more pay or
additional hours to compensate for night work).
```

Stance detection: the writer perspective

```
Conll-Format and annotations (p for pro)

1 Es es PRO PPER 3|Sg|Neut|Nom 2 subj _ _
2 muss müssen V VMFIN 3|Sg|Pres|Ind 0 root _ _
3 jedoch jedoch ADV ADV _ 5 adv _ _
4 sicher sicher ADV ADJD Pos| 5 adv _ _
5 gestellt stellen V VVPP _ 6 aux _ _
6 werden werden V VAINF _ 2 aux _ _
7 ,,$,$,_ 0 root _ _
8 dass dass KOUS KOUS _ 0 root _ _
9 die die ART ART Def|_|_|_ 10 det _ _
p10 Beschäftigen Beschäftigen N NN _|Nom|_ 13 subj _ _
11 einen eine ART ART Indef|Masc|Acc|Sg 12 det _ _
p12 Ausgleich Ausgleich N NN Masc|Acc|Sg 13 obja _ _
13 erhalten erhalten V VVPP _ 0 root _ _
14 ( ( $( $( _ 0 root _ _
15 mehr mehr ART PIAT Masc|_|Sg 16 det _ _
p16 Lohn Lohn N NN Masc|_|Sg 13 par _ _
17 oder oder KON KON _ 16 kon _ _
18 zusätzliche zusätzlich ADJA ADJA Pos|_|_|_|_| 19 attr _ _
p19 Stunden Stunde N NN _|_|_ 17 cj _ _
20 für für PREP APPR Acc 16 pp _ _
21 die die ART ART Def|Fem|Acc|Sg 22 det _ _
p22 Kompensation Kompensation N NN Fem|Acc|Sg 20 pn _ _
23 der die ART ART Def|Fem|Gen|Sg 24 det _ _
24 Nachtarbeit Nachtarbeit N NN Fem|Gen|Sg 22 gmod _ _
25 ) ) $( $( _ 0 root _ _
26 . . $. $. _ 0 root _ _
```

Stance detection: the writer perspective

- 'Beschäftigten' is neutral
- 'mehr Lohn' is not per se positive
- 'Nachtarbeit' might have a negative connotation

How can reproduce the annotation:

- p10 Beschäftigten
- p12 Ausgleich
- p16 Lohn
- p19 Stunden
- p22 Kompensation

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Model

- Embedding encodes connotation of word, but not polarity (directly)
- why not contextualize by building pairs
- target word: the one whose polarity we would like to predict
- source word: a word from the lexicon whose polarity we known
- oov 356 of all 6718 nouns from xstance texts
- overlap with polex: 1501
- we use BERT and a simple own Model

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Algorithm

we know the polarity of each xstance noun

- pair every noun from a xstance text with all noun within a given window
- pair every xstance noun with n nouns from the polarity lexicon (same polarity)
- a pair e.g. (Wochen, Mitarbeiter, 2) i.e. a neutral word pair
- determine wheter a given pair is a positive, negative or neutral pair
- split into 3 sets, do cross validation
- we get 50'000 pairs for training, 25'000 for testing

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Model

```python
class transformer(nn.Module):

    def __init__(self, k):
        super().__init__()

        self.ff = nn.Sequential(
          nn.Linear(k , k),
        #  nn.Dropout(0.25),
          nn.ReLU(),
          nn.LayerNorm(k),
          nn.Linear(k, 3))

    def forward(self, x):

        x = x.unsqueeze(dim=0)

        x=self.ff(x)

        x= F.max_pool2d(x,kernel_size=(2,1))

        m=nn.Softmax(dim=3)
        x=m(x)

        return x.squeeze(dim=2)
```

Ablation: stepwise withdrawal of components (features)

Bert result

```
3 fold crossvalidation

fold 1
rec: neg,neut,pos 0.7162162162162162 0.8761440803070564 0.8759381898454747
prec: neg,neut,pos 0.6799342105263158 0.9098574275640043 0.8435374149659864
f: 0.6976037799527506 0.8926825599759345 0.859432531947152

acc: 0.8579665803718522

fold 2

rec: neg,neut,pos 0.6896896896896897 0.8888243831640058 0.8778558875219684
prec: neg,neut,pos 0.7475587703435804 0.9104289006169628 0.8202932551319648
f: 0.7174592155501562 0.8994969338669995 0.8480989630707659

acc: 0.861172856969648


fold 3

rec: neg,neut,pos 0.7296660117878192 0.8757424947824691 0.8961905739809015
prec: neg,neut,pos 0.692910447761194 0.9062967270310683 0.8707102952913008
f: 0.7108133971291865 0.8907576747224036 0.8832667105196579

acc: 0.868765661628001


mean accuracy= 0.8626350329898337
```

Stancer: Bert-like performance

```
xstance as shown in the figure

fold 1

rec: neg,neut,pos 0.7615748031496063 0.874794304929527 0.8894960534304797
prec: neg,neut,pos 0.7217910447761194 0.9159487602067571 0.8505079825834543
f: 0.7411494252873564 0.8948986313401156 0.8695652173913043

acc: 0.8668713471924243


fold 2

rec: neg,neut,pos 0.7553571428571428 0.8773236788971663 0.8919553728714034
prec: neg,neut,pos 0.750887573964497 0.9265441176470588 0.8203715705335926
f: 0.7531157270029673 0.9012623824339305 0.8546671918077984

acc: 0.8664532357649211

fold 3
rec: neg,neut,pos 0.7785688857244571 0.8713734567901235 0.8852693924340849
prec: neg,neut,pos 0.6731301939058172 0.9019968051118211 0.8852693924340849
f: 0.7220204688015847 0.8864207221350079 0.8852693924340849

acc: 0.8669817433395587


mean accuracy= 0.8667687754323014
```

Stancer: no normalization

```
without normalization

fold 1

rec: neg,neut,pos 0.18393700787401573 0.8370895041854475 0.7379073062133171
prec: neg,neut,pos 0.6128016789087093 0.7858150312311102 0.6515368120085776
f: 0.2829457364341085 0.8106422781126584 0.6920375818544179

acc: 0.7241251757046682

fold 2

rec: neg,neut,pos 0.12351190476190477 0.8561581842233517 0.7462125660598943
prec: neg,neut,pos 0.7518115942028986 0.8040408003138486 0.6114318706697459
f: 0.2121676891615542 0.8292814512593991 0.6721320145977681

acc: 0.7266559951215794

fold 3

rec: neg,neut,pos 0.2221431114275543 0.8402006172839506 0.7246847535345816
prec: neg,neut,pos 0.6058252427184466 0.7569164465452524 0.7010442657795029
f: 0.325084657462881 0.7963870401521246 0.7126685142561886

acc: 0.727941456721424

mean accuracy= 0.7262408758492237
```

Stancer: dropout outdropped

```
without drop-out, but with normalization

fold 1

rec: neg,neut,pos 0.8125984251968504 0.8579809687343493 0.890507994333131
prec: neg,neut,pos 0.6816380449141347 0.9254514585584195 0.8551161208823244
f: 0.7413793103448275 0.8904399480230184 0.8724532791354781

acc: 0.8645409484353037

fold 2

rec: neg,neut,pos 0.7803571428571429 0.8670194249112303 0.875396359365825
prec: neg,neut,pos 0.6971550119649029 0.9202630801064144 0.8333147009502515
f: 0.7364134250807471 0.8928481806775408 0.8538373424971363

acc: 0.8586401402545926

fold 3

rec: neg,neut,pos 0.8316126735493058 0.8460648148148148 0.899885364921666
prec: neg,neut,pos 0.6772977674688315 0.9179573043114274 0.8687632574010883
f: 0.746564397571109 0.8805460750853242 0.8840504903570925

acc: 0.8659907763844952

mean accuracy= 0.8630572883581303

not much variation, we don't need dropout
```

Stancer: without RELu

```
fold 1

rec: neg,neut,pos 0.2692913385826772 0.8073263218144094 0.7591580651689941
prec: neg,neut,pos 0.5473751600512163 0.8118569681272034 0.6482329560183185
f: 0.36098796706776437 0.8095853063567227 0.6993241668608716

acc: 0.7265295553747133

fold 2

rec: neg,neut,pos 0.2386904761904762 0.8349230662117942 0.7275396359365826
prec: neg,neut,pos 0.5082382762991128 0.818063987993724 0.6194380561943805
f: 0.3248278655326043 0.8264075528909104 0.6691510045366169

acc: 0.723721320222578

fold 3

rec: neg,neut,pos 0.3456746173015308 0.7958333333333333 0.7371035536874283
prec: neg,neut,pos 0.4641491395793499 0.7805948686899266 0.7058177826564215
f: 0.3962456641501734 0.7881404500821457 0.7211214953271028

acc: 0.7242062735831079

mean accuracy= 0.7248190497267997
```

Stancer: without softmax and drop-out, but normalization and RELu

```
w
fold 1

rec: neg,neut,pos 0.7738582677165354 0.885669313872791 0.8697632058287796
prec: neg,neut,pos 0.7241379310344828 0.9041706230370317 0.8638190954773869
f: 0.7481729598051157 0.8948243458146595 0.8667809600645422

acc: 0.8667233853665754

fold 2

rec: neg,neut,pos 0.7559523809523809 0.8979321868690385 0.8749266001174398
prec: neg,neut,pos 0.7501476668635558 0.9152650628060464 0.850359547996804
f: 0.7530388378298252 0.9065157798552049 0.8624681639268349

acc: 0.872284472901898

fold 3

rec: neg,neut,pos 0.7892488430046279 0.8898148148148148 0.8856515093618648
prec: neg,neut,pos 0.7117174959871589 0.9027712541099108 0.8959219172787012
f: 0.7484807562457799 0.8962462112380508 0.8907571099154498

acc: 0.8773868963677249

mean accuracy= 0.8721315848787329
```

Problematic cases

- 440 out of 2500 lemmas (of 6700 word forms of 1000 xstance texts) do not have a single polarity
- i.e. depending on the context they are positive,negative or neutral
- e.g. 'Schweiz' has frequence 111 and we find any polarity for it (mostly positive, though)
- how do we perform on those cases

- accuracy: 0.7537

Conclusion: a very good performance on a difficult task, only by contextualization