

Problem 1:

a) Opinions:

**Classmate 1:**

- The battery lasts all day, which I love.
- The camera quality isn't as good as expected.
- It's okay for basic use.

**Classmate 2:**

- The screen resolution is fantastic.
- It's way too expensive for what it offers.
- The apps sometimes crash.

**Classmate 3:**

- The phone is very lightweight and easy to carry.
- The software is confusing to navigate.
- Overall, it's decent but not exceptional.

b) Raters:

Opinion	Rater 1	Rater 2	Rater 3
Battery lasts all day.	P	P	O
Camera not as good as expected.	N	N	N
Okay for basic use.	O	O	P
Screen resolution is fantastic.	P	P	P
Too expensive.	N	N	N
Apps crash.	N	N	O
Lightweight and easy to carry.	P	P	P
Software confusing.	N	O	O
Decent but not exceptional.	O	O	O

c) Kappa:

('kappa\_12', 0.8333333333333334)

('kappa\_13', 0.5)

('kappa\_23', 0.6666666666666667)

d) Personally, I would just use Python's built-in function to calculate:

	Rater 1	Rater 2	Rater 3
Rater 1	1.000000	0.933257	0.777714
Rater 2	0.933257	1.000000	0.833333
Rater 3	0.777714	0.833333	1.000000

- **Rater 1** and **Rater 2** have a very strong positive correlation 0.93.
- **Rater 1** and **Rater 3** have a moderately strong positive correlation 0.78.
- **Rater 2** and **Rater 3** have a strong positive correlation 0.83.

This suggests that raters largely agree, but there are some differences, particularly involving Rater 3.

Problem 2:

Sentiment lists: SentiWordNet, NRC Word-Emotion Association Lexicon, LIWC-22

SentiWordNet:

- Positive: delight, encourage, brilliant, friendly, charming, prosper, admire, hope, secure, gentle
- Negative: cry, disrupt, danger, dull, ignorant, harm, worry, rejection, bleak, panic

NRC:

- Positive: happy, cheerful, love, success, sunshine, grateful, joy, celebration, peace, trust
- Negative: sad, angry, hate, failure, gloomy, regret, fear, pain, loss, betrayal

SentiWordNet Positive to Negative/Neutral:

1. Delight: I was delighted to find the sink full of dirty dishes.
2. Encourage: Your encouragement makes me change my opinion upside down.
3. Brilliant: His brilliant plan almost got us arrested.
4. Friendly: His friendly hatred got us confused.
5. Charming: The snake was so charming that we had to leave to find an antidote.
6. Prosper: Despite their best efforts, the business failed to prosper.

7. Admire: I admire your stupidity.
8. Hope: I hope he slips and breaks his leg.
9. Secure: I feel as secure as a plane crashing.
10. Gentle: He gently cut my finger off.

SentiWordNet Negative to Positive/Neutral:

1. Cry: I almost cry after hearing his kind words.
2. Disrupt: Sometimes, a little disruption can lead to innovative solutions.
3. Danger: He is as in danger as the most secure panic room.
4. Dull: A dull moment can be a perfect opportunity for reflection.
5. Ignorant: Being ignorant of a problem can sometimes be a blessing in disguise.
6. Harm: The harm he had on you was unseen.
7. Worry: Worrying about yourself shall bring you only good.
8. Rejection: The best thing that happened is the rejection from my brat ex.
9. Bleak: He was bleak right when I needed for someone to be.
10. Panic: After she kissed me, I panicked and kissed her again, which got me a wife.

NRC Positive to Negative/Neutral:

1. Happy: She was as happy as the day her father left.
2. Cheerful: He was cheerful enough to get his hopes too high up.
3. Love: She was in love with a serial killer.
4. Success: His success was just like the division graph for values  $\geq 0$ .
5. Sunshine: The sunshine left her with major burns.
6. Grateful: He was so grateful for his toys that he threw them away.
7. Joy: I shouldn't have had encountered the joy he brought upon myself.
8. Celebration: The celebration was too early.
9. Peace: Peace got me k\*\*led.
10. Trust: That level of trust was expected from a traitor.

NRC Negative to Positive/Neutral:

1. Sad: Me, sad, on what universe?
2. Angry: I was as angry as my dad's friendly dog.
3. Hate: I hate how good this looks on you.
4. Failure: Your doctor son must be your biggest failure.
5. Gloomy: A gloomy day is a perfect time for creativity.
6. Regret: I regret to inform you that we'll give you a bigger salary, not the one expected.
7. Fear: The fear of mediocrity drove her to excel in her studies.
8. Pain: She learned valuable lessons from the pain of heartbreak.

9. Loss: I experienced the loss of only the things that needed to be lost.

10. Betrayal: Betrayal can lead to a deeper understanding of oneself.

The idea is that most of them are ironically speaking or in a opposite sense speaking or neutral in the sense that you don't know the inside context of something.

### Problem 3:

- Reduces the noise in the dataset, focusing more on words that give an actual representation of the sentiment.
- But something weird is happening, only for the smaller dataset works, not the bigger one for some reason, maybe because there is less data to train and test on.

```
Using all words as features, train on 29 instances, test on 10 instances
accuracy: 0.5
pos precision: 0.2
pos recall: 0.5
neg precision: 0.8
neg recall: 0.5
Most Informative Features
. = None          pos : neg = 4.2 : 1.0
an = True         pos : neg = 4.2 : 1.0
even = True       pos : neg = 4.2 : 1.0
go = True         pos : neg = 4.2 : 1.0
he's = True       pos : neg = 4.2 : 1.0
movies = True     pos : neg = 4.2 : 1.0
or = True         pos : neg = 4.2 : 1.0
rings = True      pos : neg = 4.2 : 1.0
than = True       pos : neg = 4.2 : 1.0
is = True         pos : neg = 2.7 : 1.0

Using filtered words as features, train on 29 instances, test on 10 instances
accuracy: 0.6
pos precision: 0.25
pos recall: 0.5
neg precision: 0.8333333333333334
neg recall: 0.625
Most Informative Features
. = None          pos : neg = 4.2 : 1.0
even = True       pos : neg = 4.2 : 1.0
go = True         pos : neg = 4.2 : 1.0
he's = True       pos : neg = 4.2 : 1.0
movies = True     pos : neg = 4.2 : 1.0
rings = True      pos : neg = 4.2 : 1.0
make = True       pos : neg = 2.5 : 1.0
movie = True      pos : neg = 2.5 : 1.0
one = True        pos : neg = 2.5 : 1.0
```

```
Using all words as features, train on 7998 instances, test on 2666 instances
accuracy: 0.77344336084021
pos precision: 0.7881422924901186
pos recall: 0.7479369842460615
neg precision: 0.7601713062098501
neg recall: 0.7989497374343586
Most Informative Features
engrossing = True   pos : neg = 17.0 : 1.0
quiet = True        pos : neg = 15.7 : 1.0
mediocre = True     neg : pos = 13.7 : 1.0
absorbing = True    pos : neg = 13.0 : 1.0
portrait = True     pos : neg = 12.4 : 1.0
flaws = True        pos : neg = 12.3 : 1.0
inventive = True    pos : neg = 12.3 : 1.0
refreshing = True   pos : neg = 12.3 : 1.0
refreshingly = True pos : neg = 11.7 : 1.0
triumph = True      pos : neg = 11.7 : 1.0

Using filtered words as features, train on 7998 instances, test on 2666 instances
accuracy: 0.7618154538634658
pos precision: 0.7612275449101796
pos recall: 0.7629407351837959
neg precision: 0.762406015037594
neg recall: 0.7606901725431358
Most Informative Features
engrossing = True   pos : neg = 17.0 : 1.0
quiet = True        pos : neg = 15.7 : 1.0
mediocre = True     neg : pos = 13.7 : 1.0
absorbing = True    pos : neg = 13.0 : 1.0
portrait = True     pos : neg = 12.4 : 1.0
flaws = True        pos : neg = 12.3 : 1.0
inventive = True    pos : neg = 12.3 : 1.0
refreshing = True   pos : neg = 12.3 : 1.0
refreshingly = True pos : neg = 11.7 : 1.0
triumph = True      pos : neg = 11.7 : 1.0
```