Solved exercises for 'Probabilistic Graphical Models: Principles and techniques'

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Contents

2 Foundations

2.1 Exercise 2.1

2.1.1 (a) $P(\emptyset) = 0$

From the axioms and set theory:

$$\emptyset, \Omega \in \mathcal{S}, \emptyset \cap \Omega = \emptyset \Rightarrow P(\emptyset \cup \Omega) = P(\emptyset) + P(\Omega) \tag{1}$$

$$P(\Omega) = 1 \tag{2}$$

$$\emptyset \cup \Omega = \Omega \tag{3}$$

With (2) and (3) we got

$$P(\Omega) = P(\emptyset \cup \Omega) = 1 \Rightarrow^{(1)} P(\emptyset \cup \Omega) = P(\emptyset) + P(\Omega) = 1 \Rightarrow P(\emptyset) = 1 - P(\Omega) =^{(2)} 0$$

2.1.2 (b) If $\alpha \subseteq \beta$, then $P(\alpha) \leq P(\beta)$

Given the special case that $\alpha = \beta \Rightarrow P(\alpha) = P(\beta)$ and the inequality is directly verified.
Lets analyze the other case where $\alpha \subset \beta$ but $\alpha \neq \beta$, from the axioms and set theory we got:
Let θ be $\theta = \beta - \alpha$

$$\beta = \alpha \cup \theta \tag{1}$$

$$\alpha, \theta \in \mathcal{S}, \alpha \cap \theta = \emptyset \Rightarrow P(\alpha \cup \theta) = P(\alpha) + P(\theta) \tag{2}$$

Then $P(\beta) =^{(1)} P(\alpha \cup \theta) =^{(2)} P(\alpha) + P(\theta)$, but because $\theta \in \mathcal{S}$ we know $P(\theta) \geq 0$, therefore we reach $P(\beta) = P(\alpha) + P(\theta) \geq P(\alpha)$.

2.1.3 (c) $P(\alpha \cup \beta) = P(\alpha) + P(\beta) - P(\alpha \cap \beta)$

Let $\alpha = \alpha' \cup \theta$ and $\beta = \beta' \cup \theta$ such that $\alpha' \cap \theta = \emptyset$ and $\beta' \cap \theta = \emptyset$.
Then $\alpha \in \mathcal{S} \Rightarrow \alpha' \in \mathcal{S} \wedge \theta \in \mathcal{S}$ and the same goes for beta.
Because of set theory and the axioms we know:

$$\alpha', \theta \in \mathcal{S}, \alpha' \cap \theta = \emptyset \Rightarrow P(\alpha' \cup \theta) = P(\alpha) = P(\alpha') + P(\theta) \tag{1}$$

$$\beta', \theta \in \mathcal{S}, \beta' \cap \theta = \emptyset \Rightarrow P(\beta' \cup \theta) = P(\beta) = P(\beta') + P(\theta) \tag{2}$$

$$\alpha \cup \beta = \alpha' \cup \beta' \cup \theta \tag{3}$$

Because $(\alpha' \cup \beta') \cap \theta = \emptyset$ and $\alpha' \cap \beta' = \emptyset$ then:

$$P(\alpha' \cup \beta' \cup \theta) = P(\alpha') + P(\beta') + P(\theta) \tag{4}$$

And finally the proof:

$$P(\alpha \cup \theta) =^{(3)} P(\alpha' \cup \beta' \cup \theta)$$

$$P(\alpha \cup \theta) =^{(4)} P(\alpha') + P(\beta') + P(\theta) \iff \text{add } P(\theta) \text{ on both sides}$$

$$P(\alpha \cup \theta) + P(\theta) = P(\alpha') + P(\beta') + 2P(\theta) \iff {}^{P(\alpha')+P(\theta)=P(\alpha)}$$

$$P(\alpha \cup \theta) + P(\theta) = P(\alpha) + P(\beta') + P(\theta) \iff {}^{P(\beta')+P(\theta)=P(\beta)}$$

$$P(\alpha \cup \theta) + P(\theta) = P(\alpha) + P(\beta) \iff {}^{\theta=\alpha\cap\beta}$$

$$P(\alpha \cup \theta) = P(\alpha) + P(\beta) - P(\alpha \cap \beta)$$

2.2 Exercise 2.2

2.2.1 (a) Show that for binary random variables X, Y the event-level independence $(x^0 \perp y^0)$ implies random variable independence

		Y			
		0	1		
X	0	$P(X=0, Y=0)$	$P(X=0, Y=1)$	$P(X=0)$	
	1	$P(X=1, Y=0)$	$P(X=1, Y=1)$	$P(X=1)$	
		$P(Y=0)$	$P(Y=1)$		

We know that $x^0 \perp y^0 \iff y^0 \perp x^0$ so we need to prove $x^1 \perp y^0$, $x^0 \perp y^1$ and $x^1 \perp y^1$. Lets start with $x^1 \perp y^0$:

$$P(X=1|Y=0) = 1 - P(X=0|Y=0) \iff {}^{x^0 \perp y^0}$$

$$P(X=1|Y=0) = 1 - P(X=0) \iff {}^{\text{since } \sum_{i=0}^{1} P(X=x^i)=1 \text{ then } 1-P(X=0)=P(X=1)}$$

$$P(X=1|Y=0) = P(X=1) \tag{1}$$

$$P(X=1 \cap Y=0) = P(X=1|Y=0)P(Y=0) =^{(1)} P(X=1)P(Y=0) \Rightarrow x^1 \perp y^0$$

The same goes for $y^1 \perp x^0$. Now we prove $x^1 \perp y^1$:

$$P(X=1|Y=1) = 1 - P(X=0|Y=1) =^{X=0 \perp Y=1} 1 - P(X=0) = P(X=1) \tag{2}$$

$$P(X=1 \cap Y=1) = P(X=1|Y=1)P(Y=1) =^{(2)} P(X=1)P(Y=1) \Rightarrow x^1 \perp y^1$$

We have proven $X=x \perp Y=y$ for all values $x \in Val(X), y \in Val(Y)$ therefore $X \perp Y$.

2.2.2   (b) Show a counterexample for nonbinary variables

		Y		
		0	1	
	0	0.1	0.1	0.2
X	1	0.1	0.4	0.5
	2	0.3	0.0	0.3
		0.5	0.5	

Here we can see that $P(X = 0|Y = 0) = \frac{P(X=0,Y=0)}{P(Y=0)} = \frac{0.1}{0.5} = 0.2 = P(X = 0)$
therefore $X = 0 \perp Y = 0$. Les see what happens for $P(X = 1|Y = 1)$:

$$P(X = 1|Y = 1) = \frac{P(X = 1, Y = 1)}{P(Y = 1)} = \frac{0.4}{0.5} = 0.8 \neq P(X = 1) = 0.5$$

We have found one tuple $x \in Val(X), y \in Val(Y)$ where $X = x \not\perp Y = x$
therefore $X \not\perp Y$.

2.2.3   (c) Is it the case that, for a binary-valued variable Z we have that $(X \perp Y|z^0)$ implies $(X \perp Y|Z)$?

No, here is a counterexample:

		Y		
		0	1	
	0	0.15	0.15	0.3
X	1	0.15	0.15	0.3
		0.3	0.3	

Table 1: Joint distribution for z=0, with $P(z = 0) = 0.6$

		Y		
		0	1	
	0	0.1	0.2	0.3
X	1	0.1	0.0	0.1
		0.2	0.2	

Table 2: Joint distribution for z=1, with $P(z = 1) = 0.4$

Lets find $P(X = x \cap Y = y|z^0)$:

$$P(X = x \cap Y = y|z^0) = \frac{P(X = x, Y = y, z = 0)}{P(z = 0)} = \frac{0.15}{0.6} = 0.25 \quad (1)$$

Lets remember $(X \perp Y|z^0) \iff P(X = x \cap Y = y|z^0) = P(X = x|z^0) * P(Y = y|z^0)$:

$$P(X = x|z^0) * P(Y = y|z^0) = \frac{0.3}{0.6} * \frac{0.3}{0.6} = 0.25 =^{(1)} P(X = x \cap Y = y|z^0)$$

So this example satisfies the hypothesis that $(X \perp Y|z^0)$, but for example:

$$P(X = 0 \cap Y = 1|z^1) = \frac{P(X = 0, Y = 1, Z = 1)}{P(Z = 1)} = \frac{0.2}{0.4} = 0.5 \qquad (2)$$

$$P(X = 0|z^1) * P(Y = 1|z^1) = \frac{0.3}{0.4} * \frac{0.2}{0.4} = \frac{3}{8} \qquad (3)$$

We know that $(X \perp Y|Z) \iff (X = x \perp Y = y|Z = z)$ for every $x \in Val(X), y \in Val(Y), z \in Val(Z)$. Also $(X = 0 \perp Y = 1|Z = 1) \iff P(X = 0 \cap Y = 1|z^1) = P(X = 0|z^1) * P(Y = 1|z^1)$ but $P(X = 0 \cap Y = 1|z^1) = 0.5 \neq P(X = 0|z^1) * P(Y = 1|z^1) = \frac{3}{8}$ therefore $(X = 0 \not\perp Y = 1|Z = 1)$.
I have found a case where $(X = 0 \not\perp Y = 1|Z = 1) \Rightarrow (X \not\perp Y|Z)$ given $(X \perp Y|z^0)$.

2.3 Exercise 2.3

2.3.1 $\alpha \cap \beta$

$$P(\alpha \cap \beta) = P(\alpha|\beta) * P(\beta) \qquad (1)$$

Lets find the minimum, if $\alpha \cap \beta = \emptyset$:

$$P(\alpha \cap \beta) = 0$$

Since $P(a) \geq 0$ for all $a \in \mathcal{S}$ then $P(\alpha \cap \beta) < 0$ is not possible therefore $P(\alpha \cap \beta) \geq 0$. Lets fint the maximum, particularly if $\alpha = \beta$:

$$P(\alpha \cap \beta) = P(\alpha) = P(\beta)$$

Since $0 \leq P(\alpha|\beta) \leq 1$ then $P(\alpha \cap \beta) =^{(1)} P(\alpha|\beta) * P(\beta) \leq P(\beta)$ therefore the particular case when $\alpha = \beta$ produces the maximum then $P(\alpha \cap \beta) \leq P(\alpha) = P(\beta)$.

2.3.2 $\alpha \cup \beta$

We have proven in exercise 2.1 that:

$$P(\alpha \cup \beta) = P(\alpha) + P(\beta) - P(\alpha \cap \beta) \qquad (1)$$

$P(\alpha)$ and $P(\beta)$ are known, we can only minimize and maximize $P(\alpha \cap \beta)$.
The minimum occurs when $\alpha = \beta$ and $P(\alpha \cap \beta) = P(\alpha) = P(\beta)$.
The maximum occurs when $\alpha \cap \beta = \emptyset$.

2.4 Exercise 2.4

2.4.1 $P(\cdot|\alpha) \geq 0$

$$P(\cdot|\alpha) = \frac{P(\cdot \cap \alpha)}{P(\alpha)}$$

But we know $\cdot \cap \alpha$ is in the event space then because of the same definition $P(\cdot \cap \alpha) \geq 0$ and we know that $P(\alpha) > 0$. So $P(\cdot|\alpha) \geq 0$.

2.4.2 $P(\Omega|\alpha) = 1$

$$P(\Omega|\alpha) = \frac{P(\Omega \cap \alpha)}{P(\alpha)} =_{\Omega \cap \alpha = \alpha} \frac{P(\alpha)}{P(\alpha)} = 1$$

2.4.3 $\beta, \gamma \in \mathcal{S}, \beta \cap \gamma = \emptyset \Rightarrow P(\beta \cup \gamma|\alpha) = P(\beta|\alpha) + P(\gamma|\alpha)$

$$P(\beta \cup \gamma|\alpha) = \frac{P((\beta \cap \alpha) \cup (\gamma \cap \alpha))}{P(\alpha)} \tag{1}$$

Because of set theory:
$$\beta \cap \alpha \subset \beta, \gamma \cap \alpha \subset \gamma \tag{2}$$
$$\beta, \gamma, \alpha \in \mathcal{S} \Rightarrow (\beta \cap \alpha) \in \mathcal{S}, (\gamma \cap \alpha) \in \mathcal{S}, \tag{3}$$
$$(\beta \cap \alpha) \cap (\gamma \cap \beta) \subset_{(2)} \beta \cap \alpha = \emptyset \Rightarrow (\beta \cap \alpha) \cap (\gamma \cap \beta) = \emptyset \tag{4}$$

Then with (3) and (4) in (1):

$$\frac{P((\beta \cap \alpha) \cup (\gamma \cap \alpha))}{P(\alpha)} =_{(3),(4)} \frac{P(\beta \cap \alpha)}{P(\alpha)} + \frac{P(\gamma \cap \alpha)}{P(\alpha)} = P(\beta|\alpha) + P(\gamma|\alpha)$$

2.5 Exercise 2.5

We say that P satisfies $(\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z})$ when $(\boldsymbol{X} = \boldsymbol{x} \perp \boldsymbol{Y} = \boldsymbol{y}|\boldsymbol{Z} = \boldsymbol{z})$. for all $\boldsymbol{x} \in Val(\boldsymbol{X}), \boldsymbol{y} \in Val(\boldsymbol{Y}), \boldsymbol{z} \in Val(\boldsymbol{Z})$

We also know that $(\boldsymbol{X} = \boldsymbol{x} \perp \boldsymbol{Y} = \boldsymbol{y}|\boldsymbol{Z} = \boldsymbol{z})$ if and only if $P(X = x \cup Y = y|Z = z) = P(X = x|Z = z)P(Y = y|Z = z)$

2.5.1 $P(X,Y|Z) = P(X|Z)P(Y|Z) \iff (\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z})$

For all $\boldsymbol{x} \in Val(\boldsymbol{X}), \boldsymbol{y} \in Val(\boldsymbol{Y}), \boldsymbol{z} \in Val(\boldsymbol{Z})$:

$$P(X = x \cup Y = y|Z = z) =_{\text{condition}}$$

$$P(X = x|Z = z)P(Y = y|Z = z) \iff {}_{\text{event conditional independence}}$$

$$(X = x \perp Y = y|Z = z)$$

Above we have that:

$$(X = x \perp Y = y|Z = z) \text{ for all } \boldsymbol{x} \in Val(\boldsymbol{X}), \boldsymbol{y} \in Val(\boldsymbol{Y}), \boldsymbol{z} \in Val(\boldsymbol{Z})$$

Which is the definition of $(\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z})$.

2.5.2 $(\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z}) \Rightarrow P(\chi) = \phi_1(\boldsymbol{X}, \boldsymbol{Z})\phi_2(\boldsymbol{Y}, \boldsymbol{Z})$

$$P(X,Y|Z) = \frac{P(X,Y,Z)}{P(Z)} = \frac{P(\chi)}{P(Z)} \Rightarrow P(\chi) = P(X,Y|Z) * P(Z)$$

$$P(\chi) = P(X,Y|Z) * P(Z) = P(X|Z)P(Y|Z)P(Z)$$

Let $\phi_1(X, Z) = P(X|Z)$ and $\phi_2(Y, Z) = P(Y|Z)P(Z)$, then:

$$P(\chi) = \phi_1(X, Z)\phi_2(Y, Z)$$

2.5.3 $P(\chi) = \phi_1(\boldsymbol{X}, \boldsymbol{Z})\phi_2(\boldsymbol{Y}, \boldsymbol{Z}) \Rightarrow (\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z})$

We have that:

$$P(Z) = \sum_x \sum_y P(\chi) = \sum_x \sum_y \phi_1(X, Z)\phi_2(Y, Z) \tag{1}$$

$$P(X,Y|Z) = \frac{P(\chi)}{P(Z)} =_{(1)} \frac{\phi_1(X, Z)\phi_2(Y, Z)}{\sum_x \sum_y \phi_1(X, Z)\phi_2(Y, Z)} \tag{2}$$

$$P(X|Z) = \frac{P(X,Z)}{P(Z)} = \frac{\sum_y P(\chi)}{P(Z)} =_{(1)} \frac{\phi_1(X, Z) \sum_y \phi_2(Y, Z)}{\sum_x \sum_y \phi_1(X, Z)\phi_2(Y, Z)} \tag{3}$$

$$P(Y|Z) = \frac{P(Y,Z)}{P(Z)} = \frac{\sum_x P(\chi)}{P(Z)} =_{(1)} \frac{\phi_2(Y, Z) \sum_x \phi_1(X, Z)}{\sum_x \sum_y \phi_1(X, Z)\phi_2(Y, Z)} \tag{4}$$

And then multiplying (3) and (4):

$$P(X|Z)P(Y|Z) = \frac{\phi_1(X,Z)\phi_2(Y,Z)(\sum_x \phi_1(X,Z))(\sum_y \phi_2(Y,Z))}{(\sum_x \sum_y \phi_1(X,Z)\phi_2(Y,Z))^2}$$

$$= \frac{\phi_1(X,Z)\phi_2(Y,Z)(\sum_x \sum_y \phi_1(X,Z)\phi_2(Y,Z))}{(\sum_x \sum_y \phi_1(X,Z)\phi_2(Y,Z))^2}$$

$$= \frac{\phi_1(X,Z)\phi_2(Y,Z)}{\sum_x \sum_y \phi_1(X,Z)\phi_2(Y,Z)} =_{(2)} P(X,Y|Z) \Rightarrow_{2.5.1} (\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z})^1$$

2.6 Exercise 2.6

$$P(X|Y) = \frac{P(X,Y)}{P(Y)} = \frac{\sum_z P(X,Y,Z=z)}{P(Y)} \qquad (1)$$

$$\sum_z P(X,Z=z|Y) = \frac{\sum_z P(X,Y,Z=z)}{P(Y)} \qquad (2)$$

And there we have that (1) is equal to (2)^2

2.7 Exercise 2.7

2.7.1 a. Prove that the weak union and contraction properties hold for any probability distribution P

[3]

Weak union $(\boldsymbol{X} \perp \boldsymbol{Y}, \boldsymbol{W}|\boldsymbol{Z}) \Rightarrow (\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z}, \boldsymbol{W})$

$$(\boldsymbol{X} \perp \boldsymbol{Y}, \boldsymbol{W}|\boldsymbol{Z}) \iff {}_{\text{proposition 2.3}} P(X,Y,W|Z) = P(X|Z)P(Y,W|Z) \quad (1)$$

$$\begin{aligned} &(\boldsymbol{X} \perp \boldsymbol{Y}, \boldsymbol{W}|\boldsymbol{Z}) \Rightarrow_{\text{decomposition}} \\ &(\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z}) \iff {}_{\text{proposition 2.3}} \\ &P(X,Y|Z) = P(X|Z)P(Y|Z) \end{aligned} \qquad (2)$$

$$\begin{aligned} &(\boldsymbol{X} \perp \boldsymbol{Y}, \boldsymbol{W}|\boldsymbol{Z}) \Rightarrow_{\text{decomposition}} \\ &(\boldsymbol{X} \perp \boldsymbol{W}|\boldsymbol{Z}) \iff {}_{\text{proposition 2.3}} \\ &P(X,W|Z) = P(X|Z)P(W|Z) \end{aligned} \qquad (3)$$

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[1]This could be also an if and only if proof so 2.5.2 wouldn't be unnecessary

[2]Actually i don't know if i can use the sum over the joint distribution for (1) but meh

[3]I had an issue with this one, i wasn't sure i could use bayes rule so i googled it, it seems that the proposition 2.3 needs that $P(Z) > 0$ and therefore bayes rule can be used

$$P(X, Y, W, Z) = P(Z)P(W|Z)P(Y|W, Z)P(X|Y, W, Z) \qquad (4)$$

$$P(X, Y|Z, W) = \frac{P(X, Y, W, Z)}{P(W, Z)} =_{(4)} P(Y|W, Z)P(X|Y, W, Z) =$$

$$P(Y|W, Z)P((X|Y, W)|Z) =_{(1)} P(Y|W, Z)P(X|Z) =_{(3)} P(Y|W, Z)P(X|Z, W)$$

Finally:

$$P(X, Y|Z, W) = P(Y|W, Z)P(X|Z, W) \iff _{\text{proposition 2.3}}(\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z}, \boldsymbol{W})$$

Contraction $(\boldsymbol{X} \perp \boldsymbol{W}|\boldsymbol{Z}, \boldsymbol{Y})$ & $(\boldsymbol{X} \perp \boldsymbol{Y}|\boldsymbol{Z}) \Rightarrow (\boldsymbol{X} \perp \boldsymbol{Y}, \boldsymbol{W}|\boldsymbol{Z})$

$$P(X, Y, W, Z) = P(Z)P(X|Z)P(Y|X, Z)P(W|X, Y, Z) \qquad (5)$$

$$P(Y, W|Z) = \frac{P(Y, W, Z)}{P(Z)} = P(Y|Z)P(W|Y, Z) \qquad (6)$$

$$P(X, Y, W|Z) = \frac{P(X, Y, Z, W)}{P(Z)} =_{(5)} P(X|Z)P(Y|X, Z)P(W|X, Y, Z) =_{X \perp Y|Z}$$

$$P(X|Z)P(Y|Z)P(W|X, Y, Z) =_{X \perp W|Z, Y} P(X|Z)P(Y|Z)P(W|Y, Z) =_{(6)} P(X|Z)P(Y, W|Z)$$

Finally:

$$P(X, Y, W|Z) = P(X|Z)P(Y, W|Z) \iff _{\text{proposition 2.3}}(\boldsymbol{X} \perp \boldsymbol{Y}, \boldsymbol{W}|\boldsymbol{Z})$$

2.7.2 *TODO* b. Prove that the intersection property holds for any positive probability distribution P

I have no idea what to do :(

2.7.3 *TODO* c. Provide a counterexample to the intersection property in cases where the distribution P is not positive

I have no idea what to do :(

2.8 Exercise 2.8

The resolution is the same as in 2.2

2.9 Exercise 2.9

Algorithm 1: Determine if a graph $\mathcal{K}$ is cyclic with BFS

Input: $\mathcal{K} = (\chi, \varepsilon)$

$visited \leftarrow \emptyset$;

for $X \in \chi \wedge X \notin visited$ **do**

    $visited \leftarrow visited \cup \{X\}$;

    for Y *such that* $(X \rightarrow Y) \in \varepsilon$ **do**

        if $Y \in visited$ **then**

            return *there is a loop*;

        end

    end

end

return *there is no loop*;

2.10 Exercise 2.10

Algorithm 2: Topological ordering over PDAG chain components

Input: $\mathcal{K} = (\chi, \varepsilon)$

$chains \leftarrow []$;

$chain\ membership \leftarrow$ empty map;

$chain\ edges \leftarrow []$;

$visited \leftarrow \emptyset$;

for $X \in \chi \wedge X \notin visited \wedge \forall(Y \rightarrow X) \in \varepsilon, Y \in visited$ **do**

    $visited \leftarrow visited \cup X$;

    $chain \leftarrow \{X\}$;

    for Y *such that* $(X\!-\!Y) \in \varepsilon$ **do**

        | $chain \leftarrow chain \cup \{Y\}$

    end

    append $chain$ to $chains$;

    for $Y \in chain$ **do**

        | $chain\ membership[Y] \leftarrow |chains|$

    end

end

for $i \leftarrow 1..|chains|$ **do**

    for Z *such that* $(Y \rightarrow Z) \in \varepsilon \wedge Y \in chains[i]$ **do**

        append $(chain\ membership[Y], chain\ membership[Z])$ to

          $chain\ edges$;

    end

end

return $chains$, *topological order over* $\mathcal{K} = (1..|chains|, chain\ edges)$;

It has linear time complexity $\mathcal{O}(|\mathcal{X}| + |\varepsilon|)$

2.11 Exercise 2.11

$$\mathbb{V}\mathrm{ar}(X) = \mathbb{E}[(X - \mathbb{E}[X])^2]$$
$$\mathbb{V}\mathrm{ar}(X) = \mathbb{E}[X^2 - 2\,\mathbb{E}[X]X + \mathbb{E}[X]^2]$$
$$\mathbb{V}\mathrm{ar}(X) = \mathbb{E}[X^2] - 2\,\mathbb{E}[X]\,\mathbb{E}[X] + \mathbb{E}[X]^2$$
$$\mathbb{V}\mathrm{ar}(X) = \mathbb{E}[X^2] - \mathbb{E}[X]^2$$

2.12 Exercise 2.12

$$\mathbb{E}[X] = \int_0^\infty xp(x) \ dx = \int_0^t xp(x) \ dx + \int_t^\infty xp(x) \ dx \geq \int_t^\infty xp(x) \ dx \geq \int_t^\infty tp(x) \ dx$$

$$\mathbb{E}[X] \geq t \int_t^\infty p(x) \ dx = tP(X \geq t)$$

2.13 Exercise 2.13

Hint: Find Y such that you can use 2.12.

$$|X - \mathbb{E}[X]| \geq t \iff (X - \mathbb{E}[X])^2 \geq t^2 \tag{1}$$

$$\mathbb{E}[(X - \mathbb{E}[X])^2] = \mathbb{V}\mathrm{ar}(X) \tag{2}$$

Let $t^2 = \alpha$ and $Y = (X - \mathbb{E}[X])^2$

$$P(|X - \mathbb{E}[X]| \geq t) =_{(1)} P((X - \mathbb{E}[X])^2 \geq t^2) = P(Y \geq \alpha)$$
$$\leq_{\mathrm{Markov's}} \frac{\mathbb{E}[Y]}{\alpha} =_{(2)} \frac{\mathbb{V}\mathrm{ar}(X)}{t^2}$$

2.14 Exercise 2.14

I can only think of doing it with moment generating functions and its also a more fun way, we need just three things:

1. $\mathcal{L}\{p_X\}(t) = M_X(-t)$

2. Let X and Y be random variables then $M_x(t) = M_y(t) \iff p_X = p_Y$

3. $M_{\alpha X + \beta} = e^{\beta t} M_X(\alpha t)$

The proof of 1. (very simple):

$$M_X(t) =_{\mathrm{definition}} \mathbb{E}[e^{tX}] = \int_{-\infty}^\infty e^{tX} p_x(x) \ dx \tag{1}$$

$$\mathcal{L}\{p_X\}(s) =_{\text{definition}} \int_{-\infty}^{\infty} e^{-sX} p_x(x) \ dx \tag{2}$$

We can see that 1. is true if we change s with $-t$ between (1) and (2).

For 2. we need to know about uniqueness of laplace transform, since p_X and p_Y are continous in all points uniqueness holds. The proof is left to the reader (? xdlol

For 3 we simply have to do:

$$M_{\alpha X + \beta} = \mathbb{E}[e^{t(\alpha X + \beta))}]$$
$$M_{\alpha X + \beta} = e^{\beta t}\,\mathbb{E}[e^{t\alpha X}] = e^{\beta t} M_X(\alpha t)$$

And here we have the mgf of a $X \sim \mathcal{N}(\mu, \sigma^2)$:[4]

$$M_X(t) = \mathcal{L}\{p_X\}(-t) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2}+tx} \ dx \tag{3}$$

Here the mgf of $X' \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$:

$$M_{X'}(t) = \mathcal{L}\{p_{X'}\}(-t) = \frac{1}{a\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(x-a\mu-b)^2}{2a^2\sigma^2}+tx} \ dx \tag{4}$$

We can use the property 3 to get the mgf of $aX + b$

$$M_{aX+b}(t) = e^{bt} M_X(at) = e^{bt}\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(x-\mu)^2}{2\sigma^2}+atx} \ dx \tag{5}$$

We can make the variable change $z = \frac{x}{a} - b \iff x = az + b$ in (4) with $dx = a \ dz$:

$$M_{X'}(t) = \frac{1}{a\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(x-a\mu-b)^2}{2a^2\sigma^2}+tx} \ dx = \frac{1}{a\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(az+b-a\mu-b)^2}{2a^2\sigma^2}+t(az+b)} a \ dz$$

$$= e^{bt}\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(az-a\mu)^2}{2a^2\sigma^2}+taz} \ dz = e^{bt}\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(az-a\mu)^2}{2a^2\sigma^2}+taz} \ dz$$

$$= e^{bt}\frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{(z-\mu)^2}{2\sigma^2}+taz} \ dz$$

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[4]This was harder than i imagined, i thought that because the distribution function had an exponential it would be an easy transform, i forgot that it had the form of e^{t^2} and that its not an easy transform that can be found in tables but im already commited to this

With this change we see that (4) and (5) are the same therefore because of the property 2 given $Y = aX + b$ and $X' \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$ then $M_{X'}(t) = M_Y(t) \implies p_{X'} = p_Y \implies Y \sim \mathcal{N}(a\mu + b, a^2\sigma^2)$.