1 / 1
points

**1.**

$p(x|\theta)p(\theta)$ is a distribution over:

- ( ) $(x, \theta)$

**Correct**
$p(x|\theta)p(\theta) = p(x, \theta)$ which is a distribution over vector $(x, \theta)$

- ( ) $\theta$
- ( ) $x$

1 / 1
points

**2.**

Choose correct statements:

- [ ] $p(a \mid b) = \int p(a \mid b, c) dc$

**Un-selected is correct**

- [ ] $p(a \mid b) = \int p(a, c \mid b) dc$

**Correct**
The sum rule.

- [ ] $p(a \mid b) = \int p(a \mid b, c) p(c) dc$, when $b$ and $c$ are independent

**Correct**
$p(c \mid b) = p(c)$ when $c$ and $b$ are independent

- [ ] $p(a, b \mid c) = p(a \mid b, c) p(b \mid c)$

**Correct**

1 / 1
points

**3.**

Choose correct statements:

- [ ] $p(a \mid b, c) = p(a \mid b)p(a \mid c)$ when $b$ and $c$ are independent

**Un-selected is correct**

- [ ] $p(a \mid b, c) = \frac{p(b \mid a, c)p(a \mid c)}{\int p(b \mid a', c)p(a' \mid c)da'}$

**Correct**

- [ ] $p(a \mid b) = \frac{p(a, c \mid b)}{p(c \mid a, b)}$

**Correct**
Apply Bayes rule to $p(c \mid a, b)$

- [ ] $p(a \mid b)p(b) + p(a \mid \overline{b})p(\overline{b}) = p(a)$, for binary $b$

**Correct**
The law of total probability

- [ ] $p(a \mid b) + p(a \mid \overline{b}) = p(a)$, for binary $b$

**Un-selected is correct**

---

1 / 1
points

**4.**

Let joint probability over random variables $a, b, c$ be $p(a, b, c) = p(a|b)p(b|c)p(c)$. Are random variables $a$ and $c$ independent?

- Yes
- No

**Correct**
Let's marginalize joint probability by $b$ and we get $\int p(a, b, c)db = \int p(a|b)p(b|c)p(c)db = p(c) \int p(a|b)p(b|c)db$. Unfortunately, integral contain inside both $a$ and $c$ and it can't be decomposed into two integrals $\int f(a, b)db$ and $\int g(c, b)db$, so $a$ and $c$ is dependent.

---

1 / 1
points

**5.**

Let joint probability over random variables $a, b, c, d$ be $p(a, b, c, d) = p(a|b)p(b)p(c|d)p(d)$. Are random variables $a$ and $c$ independent?

- Yes

**Correct**
Let's marginalize joint probability by $b$ and $d$, so we get $\int p(a, b, c, d)\, db\, dd = \int p(a|b)p(b)p(c|d)p(d)\, db\, dd = = \left(\int p(a|b)p(b)\, db\right)\left(\int p(c|d)p(d)\, dd\right)$. So we decomposed it into two integrals $\int f(a, b)db$ and $\int g(c, d)dd$, so $a$ and $c$ is independent.

No

1 / 1
points

### 6.

Recall the probabilistic regression setting. In the lecture, we have proved that solving the least-squares problem with L2 regularizer $L(w) = \sum_{i=1}^{n}(w^T x_i - y_i)^2 + C\sum_{i=1}^{N} w_i^2$ is equivalent to finding the MAP estimate for $w$ with prior distribution $\mathcal{N}(w \mid 0,\, \gamma I)$. Let us now choose a prior distribution to be Laplace distribution: $p(w|0, b) = \frac{1}{(2b)^n}\prod_{i=1}^{n} \exp\left(-\frac{|w_i|}{b}\right)$ instead of Normal. Adding which of the following regularizers to the least-squares probem is equivalent to finding a MAP-estimate for such a model?

$\sum_{i=1}^{N} w_i^{\frac{1}{2}}$

$\sum_{i=1}^{N} |w_i|$

**Correct**
Let's get minus logarithm of Laplace distribution and we will get $C\sum_{i=1}^{n} |w_i| + D$, where $C$ and $D$ are some constants. We can forget about $D$ constant because it's not important when we will minimize loss function.

$\sum_{i=1}^{N} \frac{1}{|w_i|}$

$\sum_{i=1}^{N} w_i$

1 / 1
points

### 7.

For linear regression with loss function $L(w) = \sum_{i=1}^{n}(w^T x_i - y_i)^2 + C\sum_{i=1}^{N} w_i^2$ prior distribution for weights $w$ was Normal distribution $\mathcal{N}(w|0, \gamma I)$. Which prior distribution on weights is right for loss function $L(w) = \sum_{i=1}^{N}(w^T x_i - y_i)^2$ if each component of weights should be in some predefined range: $w_i \in [l, r]$?

Uniform distribution with the same limits for each component.

$$\begin{cases} \frac{1}{(b-a)^n}, \text{ if } \forall w_i \in [l, r] \\ 0, \text{ else} \end{cases}$$

p(w|a, b) = {(b−a)n

1, if ∀wi ∈ [l, r]0, else.

**Correct**
We can formulate question using equivalent loss function $L(w) = \sum_{i=1}^{N}(w^T x_i - y_i)^2 + \sum_{i=1}^{N} r(w_i)$ without limits on weights component but function

$$\begin{cases} C, \text{ if } w_i \in [l, r] \\ +\infty, \text{ else} \end{cases}$$

r(wi) = {C, if wi ∈ [l, r]+∞, else. The same regularisation we will have if we find minus logarithm of Uniform distribution.

○ Laplace distribution with zero mean and the same divergence for each component.

$p(w \mid 0, b) = \frac{1}{(2b)^n} \prod_{i=1}^{n} \exp^{-\frac{|w_i|}{b}}.$

○ Gamma distribution with the same parameters for each component.

$p(w \mid \alpha, \beta) = \frac{\beta^{n\alpha}}{\Gamma^n(\alpha)} \prod_i^n x_i^{\alpha-1} \exp^{-\beta w_i}$

---

1 / 1
points

**8.**

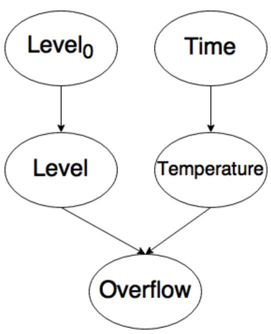
For the **remaining** problems we will use the following story:

You have a kettle that boils water. You pour water up to level $L_0$ and turn the kettle on. Over time, temperature $Temp$ starts to increase. At time $T$, level of water is $L$. Since water is boiling, water level slightly oscillates and so can be considered random. You also know that the height of a kettle is limited. If at some point water level exceeds this value, water will split on a table. We will denote this event as a binary random variable $O$ (overflow). Our goal is to determine the maximum allowed initial water level $L_{max}$ so that we can write it down in a kettle manual. Normally we would like to find $L_{max}$ for which, for example, $P(O \mid L_0 = L_{max}) = 0.001$ if you pour this amount of water, overflow will occur with a fairly low probability.

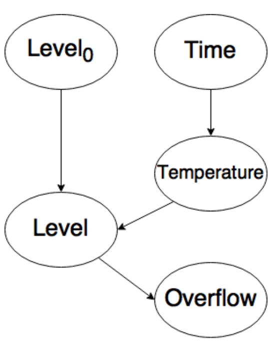
In these tasks we will construct a Bayesian network and select probability distributions needed for the model.

Our first step is to choose the correct Bayesian network.

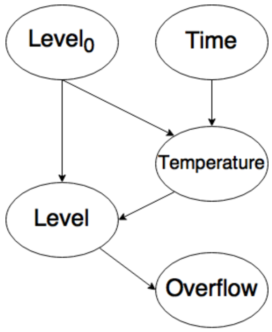
○ a)




○ b)

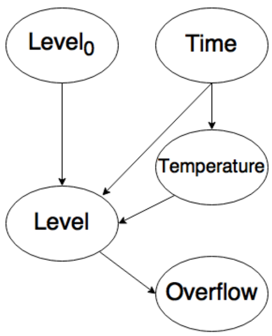



○ c)




**Correct**
Correct!

d)




1 / 1
points

**9.**

Write joint distribution for this situation.

- $p(L_0|L, Temp)p(T|Temp)p(Temp|L)p(L|O)p(O)$
- $p(O|L)p(L|L_0, Temp)p(Temp|L_0, T)p(L_0)p(T)$

**Correct**

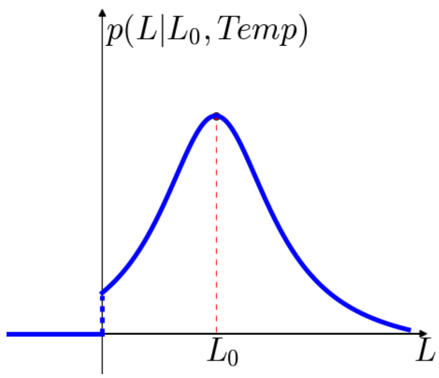
- $p(L|O)p(Temp|L_0, L)p(Temp|L_0, T)p(L_0)p(T)$
- $p(O|L)p(L|L_0, Temp)p(L_0, T|Temp)p(Temp)$

1 / 1
points

**10.**

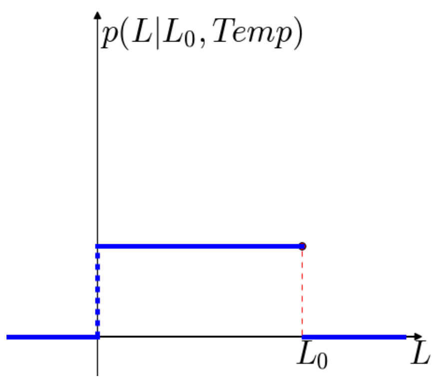
Which distribution can you use for $p(L|L_0, Temp)$?

a)

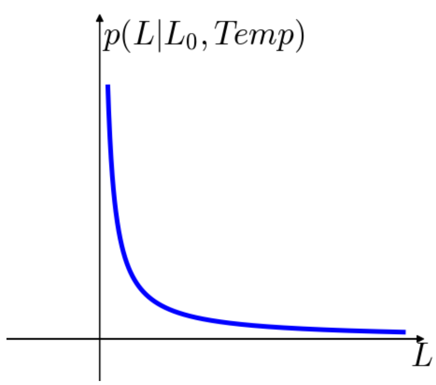



**Correct**

b)




c)



d)