Artificial Intelligence: Assignment 2

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1 Structure of the network

This graph represents the influence of the stated variables below on the **fitness potential** of an individual. On Figure 1. can be seen the causal graph related to this problem.

1.1 Variables

The graph contains exactly 10 nodes and they are explained below.

- **Age $\longrightarrow$ below 29 | 30 - 49 | over 50**
  Represents the age of the individual and could be young, middle-aged or elder.
- **Genetics $\longrightarrow$ elite | common**
  Represents whether the individual is genetically gifted to perform better or is just an average Joe.
- **Gender $\longrightarrow$ male | female**
  Represents the gender of the individual, could be male or female.
- **Training History $\longrightarrow$ consistent | inconsistent**
  Represents the consistency of the individual throughout his conscious years before the current year of his life. Consistent stands for over 51% of activity during this past period and inconsistent - below 49%.
- **Medical History $\longrightarrow$ outstanding | poor**
  Represents the overall health of the individual where illnesses, conditions and injuries are involved. The fewer of these, the better the medical history percentage would be and it would lean towards "outstanding".
- **Recovery $\longrightarrow$ sufficient | insufficient**
  Represents the overall recovery rates of the individual. Recovery has a tremendous impact on the training.

- **Sleep $\longrightarrow$ below 6h | over or at 6h**
  Represents the amount of sleep each night on average of the individual. For proper recovery are needed at least 8h of sleep per night but since most people fail to achieve that it is an interesting variable to track.

- **Nutrition $\longrightarrow$ goal-oriented | mindless**
  Represents whether the individual keeps track of his nutrition according to his goals - maintain shape, loose weight, gain muscle mass or not.

- **Fitness Potential $\longrightarrow$ positive | negative**
  Represents the rate of the fitness potential with larger positive percentage meaning better outcomes for the individual.

1.2 Objective of the network

There are a lot of speculations in the science-based fitness communities related to which factor plays key role in improving an individual's fitness potential. As an avid gym rat I modeled the problem according to my knowledge and research in this area. I track all said variables myself and try to be on top of them. I often hear different opinions of which one of them or section of them to prioritise if we cannot all (busy schedules of a student in my case prevents me to do that).

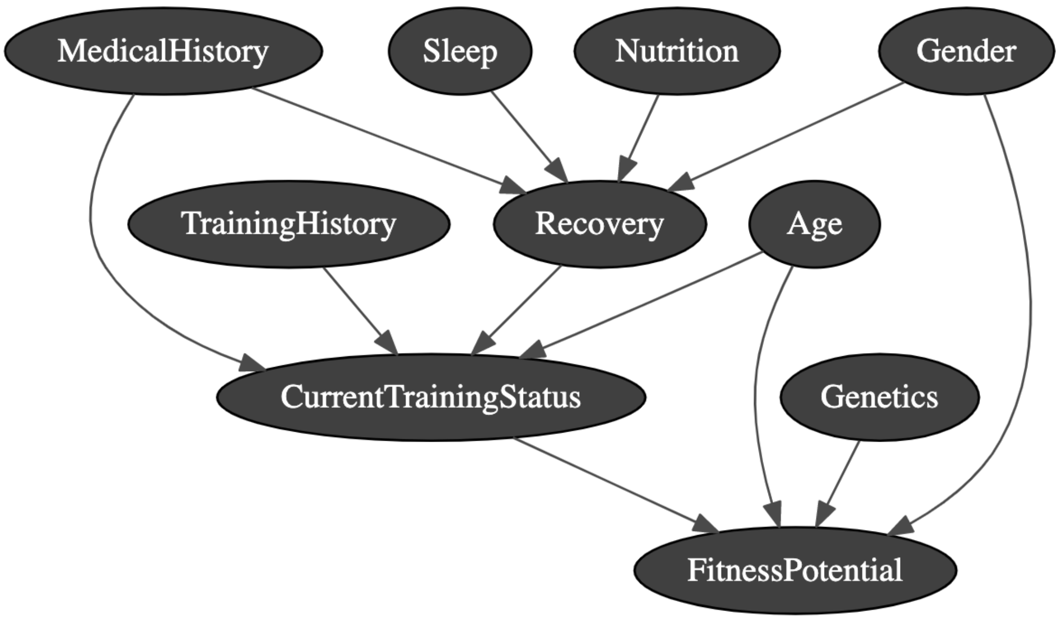

Figure 1: Causal Graph

I want to know and explore myself based on the data I know and have which of these make more of a difference. I can test if emphasising on certain ones one at a time would increase the positivity of the fitness potential. This would save me the stress of not being on top of everything and let me know if I have to slack on one of them, which one to pick.

1.3 Arcs orientation

The arcs' orientation is pretty self-explanatory, however, to clarify further - the belief is that the Sleep and Nutrition have a direct effect on the Recovery from physical exercise each day. In addition, MedicalHistory (injuries, limitations of performing certain exercises and etc) has an effect on Recovery as well (i.e. an individual has a pulled muscle, they would not be able to recover as fast as someone who is completely injury-free). This also places limitations on the consistency of the CurrentTrainingStatus as the person might need to skip this injured muscle for a given period of time. Furthermore, Recovery is also Gender-dependent because women are known to be able to handle more volume and recover faster than men.

TrainingHistory plays a pivotal role on the CurrentTrainingStatus with the belief that if someone is used to being active their whole life, it is more likely they would stick with it longterm, whereas this might not be the case for a newbie per say.

Age influences CurrentTrainingStatus as the older the person is, the expectancy of being as frequently active reduces. It also influences FitnessPotential in the way that the younger an individual is, the more potential of building a great physique they have and given they are consistent with training, their potential reduces with time (gets harder and harder to build muscle the more advanced they get).

Last but not least, Genetics are key for the amount of progress a person can achieve in a lifetime hence why it has a direct effect on FitnessPotential. Finally, FitnessPotential is Gender-dependent too with the idea that men are naturally better at training or sports because of their built.

1.4 Statistical Test

There are a lot of colliders in the graph and the most important nodes are represented by them. With that being said, in this causal graph every arc forms a v-structure and they cannot be reversed because they will break already existing v-structures. This will then result in two graphs that are not in the same equivalance class, which we aim to avoid. To conclude, there are no arcs that can be reversed as all would be detected by a statistical test.

1.5 D-Separation Analysis

I identified 4 couples of nodes that were not directly linked to each other.

- $Recovery_{and}\ FitnessPotential$

- *MedicalHistory* $_{and}$ *Nutrition*
- *TrainingHistory* $_{and}$ *Gender*
- *Sleep* $_{and}$ *CurrentTrainingStatus*

I break down these into subsections and I discuss their d-separation properties more in depth there.

1.5.1 Recovery $_{and}$ FitnessPotential

If we observe **Recovery** and **Fitness Potential** alone, we can find two paths that connect the nodes. Given that we have no prior knowledge for any of the nodes on these paths, we can clearly see that:

- **Recovery** $\longrightarrow$ **CurrentTrainingStatus** $\longrightarrow$ **FitnessPotential** is an unblocked chain and the two examined nodes are **d-connected**.
- **Recovery** $\longleftarrow$ **Gender** $\longrightarrow$ **FitnessPotential** is an unblocked fork and the two examined nodes are **d-connected**.

To d-separate them, we can condition on **CurrentTrainingStatus** but as seen on **Figure 3.** this is simply not enough for this causal graph. They would remain d-connected, unless we condition also on **Gender** which will block the remaining path and finish the job of making those two independent.

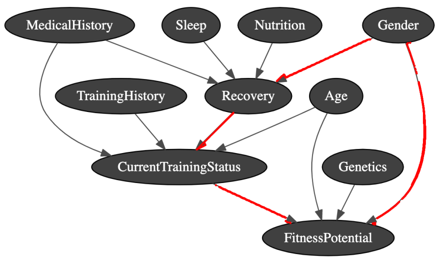

Figure 2: d-connection between Recovery and FitnessPotential without prior information

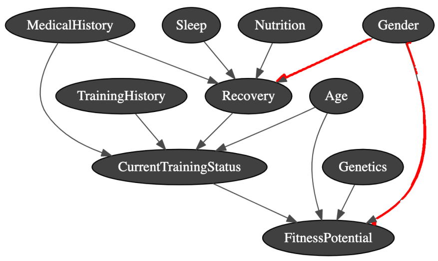

Figure 3: d-connection between Recovery and FitnessPotential conditioned on CurrentTrainingStatus

Conditioning on **CurrentTrainingStatus** as a collider, however, opens more paths (to **Medical History, Training History** and **Age** to be precise) but none of them matter to the relation of the two examined nodes as they do not belong to a path that further connects them.

1.5.2 MedicalHistory $_{and}$ Nutrition

If we observe **Medical History** and **Nutrition** alone, we can find two paths that connect the nodes. Given that we have no prior knowledge for any of the nodes on these paths, we can clearly see that:

- **Nutrition** $\longrightarrow$ **Recovery** $\longleftarrow$ **MedicalHistory** is a blocked collider and the two examined nodes are **d-separated**.
- **MedicalHistory** $\longrightarrow$ **CurrentTrainingStatus** $\longleftarrow$ **Recovery** $\longleftarrow$ **Nutiriton** is a blocked collider at **CurrentTrainingStatus** and the two examined nodes are **d-separated**.

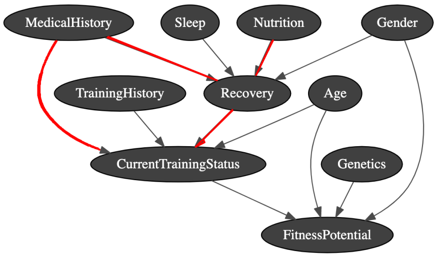

Figure 4: paths, connecting Nutrition and MedicalHistory

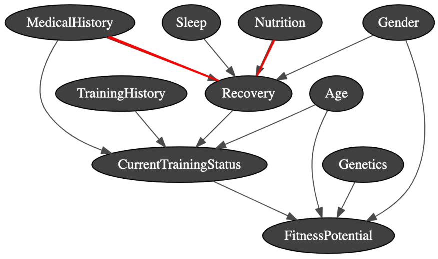

Figure 5: d-separated path between Nutrition and MedicalHistory without prior information

If we however experiment and condition on **Recovery**, we unblock this collider and since it is a parent of **CurrentTrainingStatus** and there are no other nodes on this first path, the examined nodes would be **d-connected** without any way of d-separating them anymore.

On the other hand, if we look at the second path and decide to condition on **CurrentTrainingStatus**, we open this collider but as long as **Recovery** remains unknown, MedicalHistory and Nutrition remain **d-separated**.

1.5.3 TrainingHistory $_{and}$ Gender

If we observe **Training History** and **Gender** alone, we can find two paths that connect the nodes. Given that we have no prior knowledge for any of the nodes on these paths, we can clearly see that:

- **TrainingHistory** $\longrightarrow$ **CurrentTrainingStatus** $\longleftarrow$ **Recovery** $\longleftarrow$ **Gender** is a blocked collider at **CurrentTrainingStatus** and the two examined nodes are **d-separated**.

- **TrainingHistory** $\longrightarrow$ **CurrentTrainingStatus** $\longrightarrow$ **FitnessPotential** $\longleftarrow$ **Gender** is a blocked collider at **FitnessPotential** and the two examined nodes are **d-separated**.

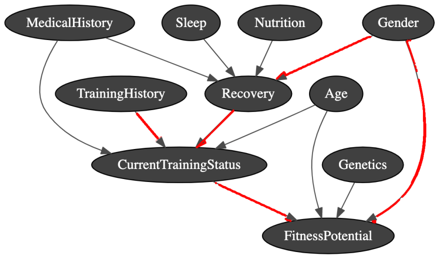

Figure 6: paths, connecting TrainingHistory and Gender

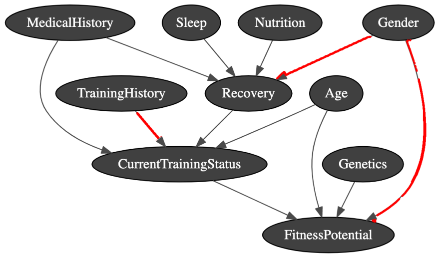

Figure 7: d-separated path between TrainingHistory and Gender conditioning on CurrentTrainingStatus and Recovery

If we however decide to experiment and condition on **CurrentTrainingStatus**, we unblock this collider and now information can flow through **CurrentTrainingStatus** $\longleftarrow$ **Recovery** $\longleftarrow$ **Gender** chain into **TrainingHistory** as after this alteration it is dependent on **Recovery** and the examined nodes are now **d-connected**.

On the other hand, if we are not satisfied with this alteration and want to d-separate once again the two examined nodes, we can simply just block the chain mentioned above by conditioning on **Recovery** (which clearly directly depends on **Gender**). As FitnessPotential is an unknown collider and we already conditioned on CurrentTrainingStatus, there are left no other paths that can let the two examined nodes influence each other as seen in **Figure 7**. With all that being said, the two examined nodes are now **d-separated** again.

1.5.4 Sleep $_{and}$ CurrentTrainingStatus

If we observe **Sleep** and **CurrentTrainingStatus** alone, we can find two paths that connect the nodes. Given that we have no prior knowledge for any of the nodes on these paths, we can clearly see that:

- **Sleep** $\longrightarrow$ **Recovery** $\longleftarrow$ **MedicalHistory** $\longrightarrow$ **CurrentTrainingStatus** is a blocked collider at **Recovery** and the two examined nodes are **d-separated**.

- **Sleep** $\longrightarrow$ **Recovery** $\longrightarrow$ **CurrentTrainingStatus** is an unblocked chain at **Recovery** and the two examined nodes are **d-connected**.

If we however decide to experiment and condition on **Recovery**, we unblock this collider and now information can flow through **Recovery** $\longleftarrow$ **MedicalHistory** $\longrightarrow$ **Current-**

TrainingStatus fork into **CurrentTrainingStatus** as after this alteration it is dependent on **Recovery** and the examined nodes are now **d-connected** as seen on **Figure 9**. At the same time for the chain path, conditioning on **Recovery** blocks the path but since there is the open collider, the two examined nodes at last remain **d-connected**.

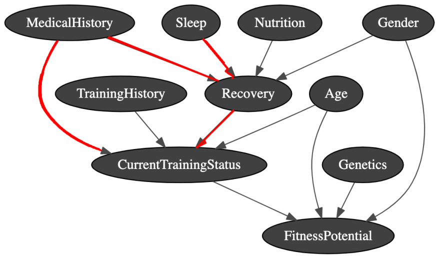

Figure 8: paths, connecting Sleep and CurrentTrainingStatus

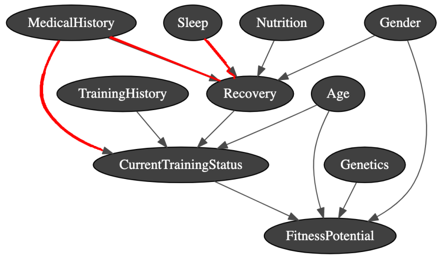

Figure 9: d-connected path conditioning on Recovery

On the other hand, if we are not satisfied with this alteration and want to d-separate fully the two examined nodes, we can simply just block the fork mentioned above by conditioning further on **MedicalHistory**. With that being said, the two examined nodes are now **d-separated**.

1.6 Real life situation

1.6.1 Recovery $_{and}$ FitnessPotential

Recovery is crucial part of increasing (if positive) or decreasing (if negative) an individual's **FitnessPotential**. The better the recovery is, the better the performance of an athlete would be in the gym and this would increase their fitness potential by making their training more optimal for muscle growth. It makes complete sense that those two are **d-connected**.

1.6.2 MedicalHistory $_{and}$ Nutrition

MedicalHistory affects more the ability of an athlete to perform certain movements, given that they suffered an injury. It makes sense that these two are **d-separated**, because there is no connection between **Nutrition** and **MedicalHistory** unless we examine in the latter deceases that prevent an individual from consuming certain types of foods or if they have any allergies but I am not taking into account such in this causal graph.

1.6.3 TrainingHistory $_{and}$ Gender

TrainingHistory is irrelevant of the **Gender** in real life as well as consistency in the gym is affected more by other real life factors that may prevent an individual from training like lack of time, lack of motivation and etc that are not taken into consideration in this graph. These could be experienced by both genders equally so it makes complete sense that we observe **d-separation** here.

1.6.4 Sleep $_{and}$ CurrentTrainingStatus

Usually one would consider **Sleep** to be very directly-affecting **CurrentTrainingStatus** but in 21^{st} century this is far from the case. As busy as life is nowadays, humans tend to juggle more than they can in just 24 hours each day. Most people don't get the 8 hours of sleep that are crucial, so even 5-6 hours per night is considered "enough" these days. I can personally attest from my past experiences that these two are as **d-separated** in this graph as they are in real life, as sleep never prevented me personally from training.

NB! That is valid if our MedicalHistory is on point, conditioned on that my observations above count as my health status is in the outstanding group.

2 Conditional probability tables (CPTs)

				FitnessPotential	
CurrentTrainingStatus	Gender	Genetics	Age	positive	negative
consistent	male	elite	below 29	0.9950	0.0050
			30 - 49	0.6500	0.3500
			above 50	0.2500	0.7500
		normal	below 29	0.9000	0.1000
			30 - 49	0.5000	0.5000
			above 50	0.1500	0.8500
	female	elite	below 29	0.9000	0.1000
			30 - 49	0.5000	0.5000
			above 50	0.1500	0.8500
		normal	below 29	0.7000	0.3000
			30 - 49	0.4000	0.6000
			above 50	0.1000	0.9000
inconsistent	male	elite	below 29	0.9000	0.1000
			30 - 49	0.6000	0.4000
			above 50	0.2000	0.8000
		normal	below 29	0.8500	0.1500
			30 - 49	0.4500	0.5500
			above 50	0.1000	0.9000
	female	elite	below 29	0.8500	0.1500
			30 - 49	0.4500	0.5500
			above 50	0.1000	0.9000
		normal	below 29	0.6500	0.3500
			30 - 49	0.3500	0.6500
			above 50	0.0500	0.9500

Figure 10: CPT for FitnessPotential

				CurrentTrainingStatus	
Recovery	MedicalHistory	Age	TrainingHistory	consistent	inconsistent
sufficient	outstanding	below 29	consistent	0.4834	0.5166
			inconsistent	0.6519	0.3481
		30 - 49	consistent	0.4709	0.5291
			inconsistent	0.9390	0.0610
		above 50	consistent	0.0302	0.9698
			inconsistent	0.2812	0.7188
	poor	below 29	consistent	0.7204	0.2796
			inconsistent	0.7019	0.2981
		30 - 49	consistent	0.6123	0.3877
			inconsistent	0.4324	0.5676
		above 50	consistent	0.5155	0.4845
			inconsistent	0.3968	0.6032
insufficient	outstanding	below 29	consistent	0.5644	0.4356
			inconsistent	0.6009	0.3991
		30 - 49	consistent	0.5203	0.4797
			inconsistent	0.3620	0.6380
		above 50	consistent	0.4088	0.5912
			inconsistent	0.7720	0.2280
	poor	below 29	consistent	0.3535	0.6465
			inconsistent	0.4112	0.5888
		30 - 49	consistent	0.7408	0.2592
			inconsistent	0.5416	0.4584
		above 50	consistent	0.5224	0.4776
			inconsistent	0.4304	0.5696

Figure 11: CPT for CurrentTrainingStatus

				Recovery	
MedicalHistory	Nutrition	Sleep	Gender	sufficient	insufficient
outstanding	goal-oriented	below 6h	male	0.4500	0.5500
			female	0.5500	0.4500
		over or at 6h	male	0.8500	0.1500
			female	0.9500	0.0500
	mindless	below 6h	male	0.4000	0.6000
			female	0.4500	0.5500
		over or at 6h	male	0.7500	0.2500
			female	0.8500	0.1500
poor	goal-oriented	below 6h	male	0.6500	0.3500
			female	0.7500	0.2500
		over or at 6h	male	0.7000	0.3000
			female	0.7500	0.2500
	mindless	below 6h	male	0.2500	0.7500
			female	0.3000	0.7000
		over or at 6h	male	0.3000	0.7000
			female	0.3500	0.6500

Figure 12: CPT for Recovery

The Conditional Probability Tables I filled out relying on studies and probabilities I observed in the past on the internet for the mass population. They are also partially based on my own experience I've gathered throughout the years of tracking these variables, knowledge and common sense. They may not be 100% correct but they make sense and are relevant for this causal graph.

3 Causal Inference

3.1 Causal effect of *CurrentTrainingStatus* on *FitnessPotential*

In this subsection I am computing the causal effect of **CurrentTrainingStatus** on **FitnessPotential** (X = *CurrentTrainingStatus* and Y = *FitnessPotential*). There are 2 confounders between the variables **Age** and **Gender**. I intervene on CurrentTrainingStatus for the incoming edges into it are surgically removed connections and then Age- and Gender-segregate with their different values in order to block all backdoor paths.

$$P(FitnessPotential \mid do(CurrentTrainingStatus)) =$$

$$= \sum_{Age,Gender} P(FitnessPotential \mid Age, CurrentTrainingStatus, Gender) \times P(Age, Gender)$$

	FitnessPotential	
CurrentTrainingStatus	positive	negative
consistent	0.6896	0.3104
inconsistent	0.6383	0.3616

Figure 13: Causal effect of *CurrentTrainingStatus* on *FitnessPotential*

As we can see on **Figure 13.** the more consistent the gym goer is the better the fitness potential they have. This is proved true also through the average causal effect in the following way:

$$P(FitnessPotential = superb \mid do(CurrentTrainingStatus = consistent))$$

$$-\ P(FitnessPotential = superb \mid do(CurrentTrainingStatus = inconsistent)) \approx 0.05$$

It is possible to do randomized control studies to disentangle this causal graph as most variables are subjective to tuning. We can assign amount of activity to an age group or gender group or combination of both and see the effect. In fact in this particular field most of the findings are done through studies and even my probability estimations are based on those. The only thing we might not be able to intervene on are the MedicalHistory and TrainingHistory.

3.2 *Age*-specific effect of *CurrentTrainingStatus* on *FitnessPotential*

In this subsection I am computing the **Age**-specific effect of **CurrentTrainingStatus** on **FitnessPotential** (X = *CurrentTrainingStatus*, Y = *FitnessPotential* and C

$= Age$). Age is a confounder for both CurrentTrainingStatus and FitnessPotential and conditioning on it alone, it blocks all other backdoor paths between the two.

		FitnessPotential	
Age	**CurrentTrainingStatus**	**positive**	**negative**
below 29	consistent	0.8753	0.1247
	inconsistent	0.8246	0.1754
30 - 49	consistent	0.4920	0.5080
	inconsistent	0.4423	0.5577
above 50	consistent	0.1469	0.8531
	inconsistent	0.0975	0.9025

Figure 14: Age-specific effect of *CurrentTrainingStatus* on *FitnessPotential*

The computation comes down to intervening on ***CurrentTrainingStatus = g(Age)*** on **FitnessPotential** and replacing that in the following equation:

$$P(FitnessPotential \mid do(CurrentTrainingStatus = g(Age))) =$$

$$= \sum_{below\ 24} P(FitnessPotential \mid do(CurrentTrainingStatus = c), Age\ =\ below\ 29)|_{c=g(below\ 29)}$$

$$\times\ P(Age\ =\ below\ 29)\ \approx\ 0.88$$

I picked a value of **consistent** for CurrentTrainingStatus and **below 29** for Age and as seen in the table and the equation above, we get a value of ≈ 0.88.

3.3 Causal Direct Effect of *MedicalHistory* on CurrentTrainingStatus mediating through *Recovery*

In this subsection I am computing the causal effect of **MedicalHistory** on **CurrenTrainingStatus** (X = *MedicalHistory* and Y = *CurrenTrainingStatus*) and my mediating variable is **Recovery**. There are two confounders Age and TrainingHistory on CurrentTrainingStatus and I adjust for them.

		CurrentTrainingStatus	
Recovery	MedicalHistory	consistent	inconsistent
sufficient	outstanding	0.8287	0.1712
	poor	0.5594	0.4406
insufficient	outstanding	0.7025	0.2975
	poor	0.4766	0.5234

Figure 15: MedicalHistory effect on CurrentTrainingStatus through Recovery

Now, to compute the controlled direct effect:

$$P(CurrentTrainingStatus \mid do(MedicalHistory),\ do(Recovery = insufficient)) =$$
$$= \sum_{Age, TrainingHistory} P(CurrentTrainingStatus \mid Age, MedicalHistory, TrainingHistory, Recovery)$$
$$\times P(Age) \times P(TrainingHistory)$$

And if we first replace in the equation above *do(MedicalHistory = outstanding)* and then substract from it the same equation but for *do(MedicalHistory = poor)*, we get a CDE of ≈ 0.17. This value makes complete sense because more injuries would mean less consistency with training.

4 Simulation

For this part of the assignment, I made **Gender** unmeasurable as seen on **Figure 13.**. I also redid the CPTs that included Gender, so that I can redo the computations of the previous point.

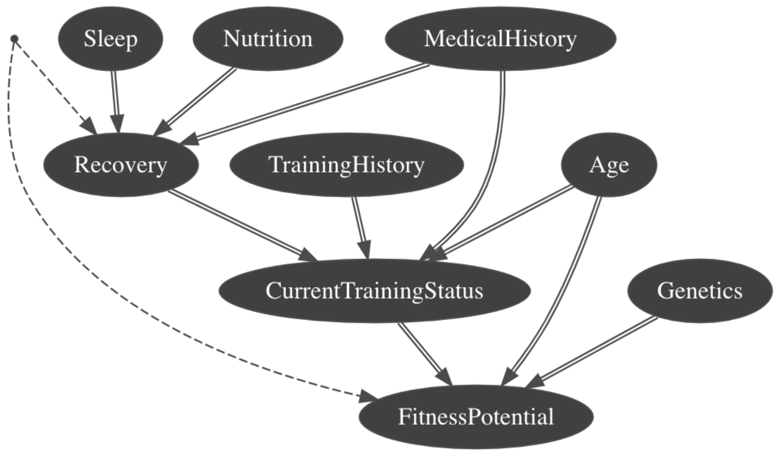

Figure 16: Modified causal graph without **Gender**

4.1 Causal effect of ***CurrentTrainingStatus*** on ***FitnessPotential***

In the previous section, **Gender** was a backdoor for **CurrentTrainingStatus** and **FitnessPotential**. To be able to compute the causal effect score again, we need to use **MedicalHistory** and **Recovery** in addition to **Age** as they are two newfound backdoors after changing the causal graph.

	FitnessPotential	
CurrentTrainingStatus	positive	negative
consistent	0.6825	0.3175
inconsistent	0.6215	0.3785

Figure 17: Causal effect of CurrentTrainingStatus on FitnessPotential with unmeasurable Gender

The causal effect can be computed now with the following modified equation from **3.1.**:

$$P(FitnessPotential \mid do(CurrentTrainingStatus)) =$$

$$= \sum_{Age, MedicalHistory, Recovery}$$

$$P(FitnessPotential \mid Age, CurrentTrainingStatus, MedicalHistory, Recovery)$$

$$\times P(Age, MedicalHistory, Recovery)$$

The average causal effect of **CurrentTrainingStatus** on **FitnessPotential** is ≈ 0.05 as previously computed.

4.2 *Age*-specific effect of *CurrentTrainingStatus* on *FitnessPotential*

In this part as said previously in **3.2** - Age is a confounder for both CurrentTrainingStatus and FitnessPotential and conditioning on it alone blocks all other backdoor paths between the two. Therefore, the computation doesn't change but the probabilities are slightly different since Gender's connection to FitnessPotential is removed.

		FitnessPotential	
Age	CurrentTrainingStatus	positive	negative
below 29	consistent	0.8818	0.1182
	inconsistent	0.8041	0.1959
30 - 49	consistent	0.5541	0.4459
	inconsistent	0.5041	0.4959
above 50	consistent	0.1924	0.8076
	inconsistent	0.1424	0.8576

Figure 18: Age-specific effect of *CurrentTrainingStatus* on *FitnessPotential*

The value of **consistent** for CurrentTrainingStatus and **below 29** for Age and as seen in the table above is ≈ 0.88, but this time it is increased by little less than 0.01.

4.3 Causal Direct Effect of *MedicalHistory* on CurrentTrainingStatus mediating through *Recovery*

Here as before I have knowledge of the two confounders Age and TrainingHistory on CurrentTrainingStatus and I simply adjust for them.

		CurrentTrainingStatus	
Recovery	MedicalHistory	consistent	inconsistent
sufficient	outstanding	0.5558	0.4442
	poor	0.6073	0.3927
insufficient	outstanding	0.5191	0.4809
	poor	0.5935	0.4065

Figure 19: MedicalHistory effect on CurrentTrainingStatus through Recovery

The values in **Figure 19.** are less assuring of the effect with Gender being removed and it has a direct impact on Recovery. Nonetheless, when we redo the computation in section **3.3** we get a CDE of ≈ 0.11 (0.06 less than pre-simulation which is very similar).

5 Results

The causal graph gave me more insight on how much the explored variables influence one another. For the most part, my prior knowledge was confirmed as true. The graph responded to all the queries in a sensible way. Something I found particularly interesting is how MedicalHistory actually plays a huge role on Recovery, because as someone who never had an injury, I never read and took into consideration the limitations it can put on the CurrentTrainingStatus.

Something very peculiar I wanted to touch on is the CDE of MedicalHistory on CurrentTrainingStatus mediating through Recovery. Everytime I run my jupyter notebook it produces different result, sometimes consistent, sometimes inconsistent. I couldn't figure out why it happens but other colleagues of mine had similar problems, so I just commented in this report one of the consistent versions of results it spit back.

The Causal Graph could be made more advanced by including additional variables like Income, Quality of Food, Cultural behaviour i.e. are tracked. Furthermore, the already existing variables can be checked for further dependencies on one another.

To be able to understand this graph fully and produce more realistic results, I would need real data (as diverse as possible) and more time to try to find hidden variables and even more importantly explore all possible connections that could directly or indirectly affect one's FitnessPotential.