本问题旨在分析在网球比赛中影响球员momentum变化的因素，试图为网球教练提供赛前建议和赛后复盘。Momentum在物理学中反映了运动的能量和趋势，在网球比赛中，如果一个运动员在当前回合士气正盛，在双方竞技水平相差不大（都参加了国际性的网球公开赛）的情况下，此士气高的运动员将极有可能拿下后面的一球甚至多球，进而影响更深层次的比赛结果。

所有的研究都基于对momentum的定量计算。我们基于过往的相关论文和经验，在第一问中建立了momentum score模型，该模型可以计算一场比赛中任何一个回合结束后双方球员momentum的定量增减，综合考虑了连续得分的线性补正、连续小局获胜的线性补正、大比分差距的指数级补正、小比分差距的线性补正，以及错失破发点、破发与被破发、拍数和双方跑动距离的影响。并采用指数移动平均平滑使momentum score变化更为平滑，方便后面的机器学习过程。在第一问的最后，我们筛选出变化程度大于一定阈值的点，这些点被认为是momentum变化较为剧烈的回合，与比赛中的实际情形十分吻合。另外，通过观察图像双方球员两条momentum曲线的变化趋势，也可以发现与比赛的整体观感非常接近。例如2024温网的总决赛，球员2（Novak Djokovic）在第一回合和第三回合分别以6-1和6-3轻松取胜，而在第二回合和第四回合则是球员2（Carlos Alcaraz）占优。最后的决胜局双发局势犬牙交错，直到最后才分出胜负，这很好地体现在了我们的momentum score模型中。

针对一些教练对momentum的变化是否是随机的质疑，我们采用了统计测试的方法来分析比赛数据。使用随机过程模拟与假设检验的方法。首先，基于实际比赛数据计算势头得分，然后通过模拟大量随机比赛来生成势头得分的分布，最后使用Kolmogorov-Smirnov测试和统计假设检验，判断出实际比赛中的势头转换显著不同于随机情况，从而否定了势头变化的随机性，理论上增强了我们模型的科学性。

基于momentum score模型。我们就可以通过寻找momentum曲线模型意义重大的交点确定比赛转折点。我们将momentum score模型得出的momentum score当作第三问预测模型的标签，选择更多的与发球回球相关的特征进行机器学习，拟合出随机森林回归器模型，取特征重要性最高的前若干个特征，再次进行机器学习。再对所有交点加上严格的条件判断，确定筛选出将比赛带入胶着或带出胶着的交点作为转折点，分析转折点在实际比赛中的合理性。通过二十余场比赛的验证，我们认为预测模型能够很好地找出比赛转折点。最后，基于这些比赛转折点，重点分析它们的比赛策略（接发球类型，球速，跑动等），给出了一般性建议。

我们也在2018澳网公开赛混双比赛的数据集上进行了泛化性分析。虽然由于数据集本身不全面，特征缺少的问题，导致预测模型无法较好地发挥性能，但依然体现出了较为不错的预测准确率，说明了我们的预测模型拥有较好的泛化能力，有希望应用与男单之外，女单，混双，甚至乒乓球、羽毛球等比赛的转折点预测任务。

我们为教练员提供了一页多的memo，为他们和他们的球员提供一定的指导意见。

The aim of this study is to analyze factors influencing momentum changes in tennis matches, seeking to offer pre-match advice and post-match analysis for tennis coaches. In physics, momentum reflects the energy and tendency of motion. In tennis matches, if a player is high in morale in the current round and there is not a significant difference in competitive level between the players (both have participated in international tennis opens), the player with higher morale is likely to win the next few points or even more, thereby affecting deeper levels of match outcomes.

All research is based on the quantitative calculation of momentum. We have established a momentum score model in the first question, based on relevant papers and experience. This model quantitatively calculates the increase or decrease in players' momentum at the end of any round in a match, taking into account linear corrections for consecutive scoring, linear corrections for consecutive set wins, exponential corrections for large score differences, linear corrections for small score differences, and the impact of missing break points, breaks and being broken, the number of strokes, and the running distance of both players. We use an exponential moving average to smooth the momentum score changes, facilitating the machine learning process. At the end of the first question, we select points where the change is above a certain threshold, considered to be rounds with significant momentum changes, highly consistent with the actual situation in the matches. Additionally, observing the trend changes in the momentum curves of both players can reveal a close correlation with the overall perception of the match. For example, in the 2024 Wimbledon final, player 2 (Novak Djokovic) easily won the first and third rounds with 6-1 and 6-3, while player 2 (Carlos Alcaraz) had the advantage in the second and fourth rounds. The final set was closely contested until the end, which is well-reflected in our momentum score model.

Addressing some coaches' skepticism about whether momentum changes are random, we used statistical testing methods to analyze match data. We employed random process simulations and hypothesis testing methods. First, we calculated the momentum scores based on actual match data, then generated distributions of momentum scores through simulating numerous random matches, and finally used the Kolmogorov-Smirnov test and statistical hypothesis testing to determine that the momentum shifts in actual matches significantly differ from random cases, thereby negating the randomness of momentum changes and theoretically strengthening the scientific nature of our model.

Based on the momentum score model, we can identify turning points in matches by finding significant intersections in the momentum curve model. We used the momentum scores derived from our model as labels for our third question's prediction model, choosing more features related to serving and returning for machine learning, and fitting a random forest regression model. Selecting the most important features, we conducted further machine learning. Applying strict conditions to all intersections, we determined turning points that either deadlock the match or break the deadlock, analyzing their rationality in actual matches. After verifying with over twenty matches, we believe the prediction model can accurately identify match turning points. Finally, based on these turning points, we analyzed key match strategies (like serve and return types, ball speed, movement, etc.) and provided general advice.

We also conducted a generalizability analysis on the 2018 Australian Open mixed doubles dataset. Although the prediction model couldn't perform optimally due to incomplete datasets and lack of features, it still demonstrated a reasonably high prediction accuracy. This suggests that our prediction model has good generalizability and could potentially be applied to predicting turning points in matches beyond men's singles, including women's singles, mixed doubles, and even in table tennis or badminton matches.

We provided coaches with a memo of over a page, offering them and their players specific guidance.