Using Clustering to Find Pitch Subtypes and Effective Pairings

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Abstract

Using Statcast data, it is now possible to compare individual pitches across baseball based on characteristics like movement, velocity, and spin rate that become obvious and meaningful even in a single outing. Various research has used those physical characteristics to define optimal pitches. In particular, previous work has studied: (i.) classifying pitches in an unsupervised manner pre- and post-Statcast, (ii.) the characteristics of an effective changeup, and (iii.) the optimal distribution of pitches. However, even an elite pitch has to be mixed with less optimal ones, especially for starting pitchers. Therefore, it is imperative to study the interactions between pitches to fully understand the best shape a particular pitch should have – how a pitch is paired with others can be as important as its own characteristics. In this work, we use clustering within given Statcast pitch types to find effective and ineffective subtype pitch pairings. To do so, we first attempt to understand how many different subtypes exist of a Statcast pitch classification by using k-means clustering of vertical and horizontal movement, velocity, and spin rate data for every pitch thrown in the 2016 and 2017 seasons. For both left-handed and right-handed pitchers, we find 30 subtypes within the 9 prominent Statcast pitch types. For example, we find 4 subtypes of changeups for right-handed pitchers and 3 for left-handed pitchers. Using these subtype clusters, we consider resulting performance based on swinging strike rate, exit velocity, and extreme launch angles (over 40 degrees and less than 0 degrees). We then consider the effectiveness of each subtype (which we refer to as the reference subtype) when paired with each of the other 29 subtypes. Next, we consider the gain or loss for all pitchers who include both the reference pitch subtype and paired pitch subtype in their pitch arsenal from the average performance of the reference pitch subtype. As a result, we find that the average gain across all pitch subtypes by the most effective pitch subtype pair increases swinging strike rate by almost 2 percent, raises extreme launch angle outcomes by over 4 percent, and reduces exit velocity by more than 1 MPH – all amounts that are similarly lost by the worst pitch subtype pairs. We visualize pitch subtypes and present specific pitcher examples of effective and ineffective pitch subtype pairing. Our work has potential impact on pitch design, player development, and scouting. For the former, teams could focus efforts on teaching young pitchers new pitch subtypes that have specific shapes according to the characteristics of the best pitches already thrown by that pitcher. For the latter, with very little in-game data, teams could seek to add pitchers that already possess effective pairings or avoid pitchers with ineffective pairings.

1 Introduction

Pitch design has advanced to the point that tinkering in a lab with high-speed, high-resolution cameras is commonplace to potentially modify the ideal shape of a given pitch. These systems capture the way in which a pitch leaves the fingers, having potential impact on the spin axis, spin rate, velocity, and resulting horizontal and vertical movement. With such fine precision, the traditional classes of pitches might be called into question since sub-classes of pitch types could be forming based on a number of minor alterations to the grip, release point, and other pitching mechanics. We could potentially rely on existing works that have studied: (i.) classifying pitches in an unsupervised manner pre- and post-Statcast by [1] and [2], (ii.) the characteristics of an effective changeup [3], (iii.) the optimal distribution of pitches [4], and (iv.) a survey of publicly available data and existing methods to evaluate pitch types and performance [5]. However, these works have not evaluated how one pitch type or subtype can affect another when a pitcher throws multiple pitches. In other words, understanding whether given a particular pitch with its physical characteristics of spin rate, velocity, and break, can have better or worse outcomes when a second pitch of different physical characteristics is paired with it.

In this paper, we use clustering within each of the most common pitch classifications as determined by Statcast to find the subtypes of pitches and evaluate their performance when paired with all other subtypes to determine if performance can increase or decrease by these pairings. While we find a differing level of subtypes for each of the 9 most common MLB pitch types for left-handed and right-handed pitchers across all pitches thrown in the 2016 and 2017 seasons, we find the total number of subtypes that result to be 30 for both types of pitchers. We consider three performance metrics of swinging strike percentage (*i.e.*, whiff rate), exit velocity (*i.e.*, how hard the ball was hit), the percentage of time the launch angle is below 0 percent (*i.e.*, ground ball rate), and the percentage of time the launch angle is above 40 percent (*i.e.*, pop-up percentage). First, we create a reference for each of these subtypes by studying the average performance of each of these 30 pitch subtypes for each handedness. We find that even within the same Statcast pitch types, there are sizable differences in effectiveness for these four performance metrics across pitch subtypes.

Then, we compare this reference performance against the performance of that same reference subtype for all occurrences where a pitcher throws that second subtype and created ordered lists according to the change in each performance metric. Hence, we found the highest and lowest performing subtype pair for whiff, pop-up, and ground ball rates and exit velocity, calling these the best and worst subtype pairings for each pitch subtype and performance metric. For example, looking at CH1 of LHP in the top left corner of Table 2 and Table 3, the highest positive difference in swinging strike rate for CH1 was when FC3 was paired with it, and the greatest negative difference in swinging strike rate for CH1 was when SI2 was paired with it. After repeating this for all reference subtypes and all possible subtype pairs across all performance metrics, we find that each of these best and worst pairing subtypes are typically distinct across these performance metrics for a given reference subtype. When we consider the average gains across each of these metrics, we find an improvement of 1.6 percent swinging strike percentage, 3.8 percent pop-up rate, 4.2 percent ground ball rate, and a reduction of 1.2 MPH on exit velocity. Conversely, by performing the same process for finding the worst pairing subtypes, we find reductions in the swinging strike rate by 1.9, pop up rate by 2.9, ground ball rate by 4.8, and increase the exit velocity by 1.2 MPH.

2 Pitch Subtype Classification Using Statcast-Driven K-Means Clustering

Major League Baseball classifies each pitch based on Statcast metrics to be immediately broadcast across various platforms from in-stadium scoreboards to the MLB AtBat application globally. While we cannot know the exact algorithms used to perform the classification, based on per pitch data from 2016 and 2017, there are 9 predominant pitch types for both right-handed and left-handed pitchers: four-seam fastball (FF), two-seam fastball (FT), cutter (FC), splitter (FS), sinker (SI), curveball (CU), knuckle curve (KC), slider (SL), and changeup (CH). Since these classifications are broad in nature, there are differences in horizontal and vertical movement, velocity, and spin rate, even within the same class of pitch. Movement of pitches is relative to a gyroball, which is a ball spinning in a spiral shape (like a football). That shape of pitch is considered the theoretical zero / zero from which other pitches are defined. Unlike a perfect gyroball, almost all pitches exhibit some form of a magnus effect, which describes the forces that deflect the ball in a particular direction based on the velocity, spin, and spin axis of the thrown ball. To understand the degree to which these four physical characteristics differ within each class, we use clustering within a four-dimensional space as represented by these four physical parameters:

- **Horizontal Movement:** From the catcher's viewpoint and with respect to the movement of a gyroball, a negative value would move toward a right-handed hitter, whereas a positive value would move toward a left-handed hitter.
- **Vertical Movement:** From the catcher's viewpoint and as compared to the movement of a gyroball, a negative value would move downward, whereas a positive value would rise.
- **Velocity:** The miles per hour that a pitch travels as measured out of the pitcher's hand.
- **Spin Rate:** The revolutions per minute along the spin axis of a particular pitch.

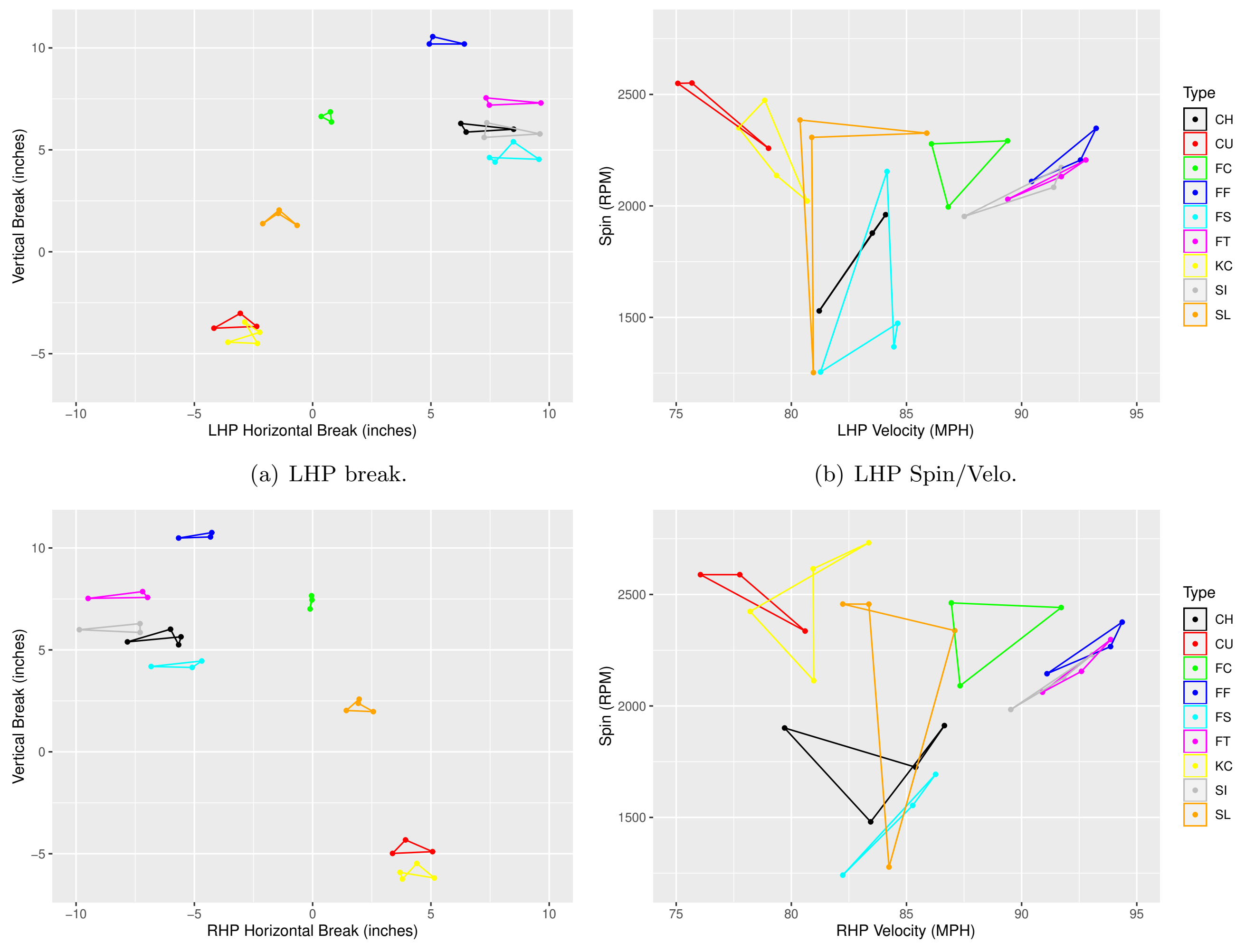
We use K-means clustering to form the clusters, meaning we partition n observations into the k clusters where there exists an n of the number of pitches thrown in 2016 and 2017 from a particular handedness from a particular MLB pitch classification. The k is determined via the elbow method where with each of the increasing k values, we evaluate the aggregate Within-Cluster-Sum-of-Squares (WCSS) error between all the data points and the k cluster centroids. In particular, over all k for a given MLB pitch type, when the WCSS value begins to flatten, an elbow is created in the curve, signaling the reduction of error by increasing the number of clusters has lessened significantly and forming the appropriate number of clusters. To ensure that each physical trait does not dominate, we scale the smallest and largest value of each field to be of comparable range.

LHP Type/Subtype	Count	SwK (%)	Exit Velo (MPH)	LA>40° (Pop-up %)	LA<0° (GB %)	Velo (MPH)	Spin (RPM)	Xbrk (in.)	Ybrk (in.)
CH	45948	15.7	81.3	16.0	37.1	83.1	1811	7.0	4.8
CH 1	18837	15.7	82.0	17.1	36.3	84.1	1961	6.3	6.3
CH 2	13286	15.9	82.2	13.9	39.9	81.2	1529	6.5	5.9
CH 3	13825	15.5	79.5	16.6	35.5	83.5	1878	8.5	6.0
CU	28233	12.5	81.5	13.0	38.8	76.7	2440	−3.0	−2.7
CU 1	6561	12.1	79.2	10.9	42.8	75.7	2551	−4.2	−3.7
CU 2	10644	13.2	82.4	16.0	33.1	79.0	2259	−3.1	−3.0
CU 3	11028	12.0	82.1	11.2	42.4	75.1	2550	−2.4	−3.7
FC	15322	10.6	82.1	16.7	32.8	87.4	2193	0.6	5.6
FC 1	5524	11.8	81.8	16.0	33.0	86.1	2278	0.8	6.4
FC 2	4876	9.4	82.2	15.9	33.5	86.8	1995	0.4	6.6
FC 3	4922	10.6	82.3	18.3	31.8	89.4	2292	0.7	6.9
FF	130063	7.7	83.1	25.4	21.7	92.2	2234	5.4	8.6
FF 1	34481	7.6	81.9	24.5	21.9	92.6	2206	6.4	10.2
FF 2	41537	5.9	84.5	21.5	26.6	90.4	2110	4.9	10.2
FF 3	54045	9.1	82.9	29.1	17.6	93.2	2348	5.1	10.6
FS	2679	18.7	81.8	16.4	38.7	83.4	1562	8.3	3.8
FS 1	503	20.1	83.9	13.3	41.0	84.6	1474	7.5	4.6
FS 2	863	20.3	83.9	11.3	42.1	81.3	1255	7.7	4.4
FS 3	719	13.9	78.9	30.0	29.4	84.2	2154	8.5	5.4
FS 4	594	21.2	79.5	11.7	42.2	84.5	1368	9.6	4.5
FT	55588	6.1	84.1	15.6	35.4	91.5	2134	8.1	5.9
FT 1	23008	7.0	85.2	18.4	32.4	92.8	2206	7.3	7.6
FT 2	15669	5.0	85.0	12.6	41.5	89.4	2030	7.5	7.2
FT 3	16911	5.8	82.0	14.8	34.1	91.7	2132	9.7	7.3
KC	8318	12.6	82.7	8.6	41.9	79.3	2229	−2.7	−3.3
KC 1	2172	12.1	83.9	8.3	40.8	78.8	2474	−2.2	−3.9
KC 2	1571	10.4	81.1	5.6	44.4	77.7	2350	−3.6	−4.4
KC 3	1994	12.2	84.2	4.6	56.9	79.4	2137	−2.3	−4.5
KC 4	2581	14.7	81.9	13.3	31.3	80.7	2022	−2.9	−3.4
SI	23387	6.8	83.7	17.1	35.9	90.8	2107	7.9	4.5
SI 1	13200	6.8	84.6	21.1	30.0	91.7	2172	7.4	6.3
SI 2	4846	6.3	84.6	8.9	47.3	87.5	1953	7.3	5.6
SI 3	5341	7.2	81.1	14.9	40.0	91.4	2083	9.6	5.8
SL	44923	15.9	81.8	17.0	33.9	83.1	2275	−1.4	1.4
SL 1	10902	16.2	79.6	18.2	32.3	80.9	2307	−2.1	1.4
SL 2	20593	15.9	82.3	17.0	35.3	85.9	2326	−1.4	2.0
SL 3	10881	15.7	82.6	15.1	33.5	80.4	2385	−0.7	1.3
SL 4	2547	15.7	83.0	18.2	30.5	81.0	1252	−1.5	1.9

RHP Type/Subtype	Count	SwK (%)	Exit Velo (MPH)	LA>40° (Pop-up %)	LA<0° (GB %)	Velo (MPH)	Spin (RPM)	Xbrk (in.)	Ybrk (in.)
CH	97836	15.0	82.1	15.0	37.8	84.3	1741	−6.3	5.5
CH 1	28814	14.1	83.5	14.1	38.4	86.6	1912	−5.6	5.6
CH 2	27372	16.0	82.8	12.1	42.9	83.4	1480	−5.7	5.3
CH 3	16232	15.3	81.2	21.4	29.1	79.7	1901	−6.0	6.0
CH 4	25418	14.7	80.5	14.9	37.7	85.4	1725	−7.8	5.4
CU	87674	12.2	81.8	13.9	36.0	78.1	2498	4.0	−4.7
CU 1	35888	10.7	82.5	12.3	38.2	76.1	2589	3.4	−5.0
CU 2	31387	13.9	82.2	16.5	32.5	80.6	2336	3.9	−4.3
CU 3	20399	12.3	80.1	12.8	37.4	77.8	2589	5.1	−4.9
FC	50020	11.4	81.9	19.6	29.6	88.7	2363	−0.1	7.3
FC 1	17663	10.8	81.3	22.7	27.2	91.7	2441	0.0	7.7
FC 2	12402	9.5	82.5	19.5	30.6	87.3	2091	0.0	7.5
FC 3	19955	13.1	82.1	17.1	31.1	86.9	2462	−0.1	7.0
FF	376138	7.9	83.6	26.1	20.6	93.1	2269	−4.7	10.6
FF 1	103554	8.0	82.1	25.2	20.8	93.9	2266	−5.7	10.5
FF 2	124287	5.8	84.6	24.2	23.3	91.1	2145	−4.3	10.5
FF 3	148297	9.4	84.0	28.7	18.1	94.4	2376	−4.3	10.8
FS	16782	17.2	82.5	13.0	40.6	84.7	1516	−5.3	4.3
FS 1	5310	18.1	82.5	14.6	36.9	82.2	1241	−5.1	4.1
FS 2	7366	16.2	83.7	11.8	44.0	86.3	1693	−4.7	4.5
FS 3	4106	18.0	80.6	13.2	39.6	85.3	1554	−6.8	4.2
FT	144139	5.7	84.5	15.6	35.1	92.4	2170	−7.9	7.7
FT 1	46996	5.7	82.2	16.0	33.8	92.6	2155	−9.5	7.5
FT 2	47317	6.5	85.7	18.4	31.5	93.9	2298	−7.2	7.9
FT 3	49826	4.9	85.7	12.5	39.9	90.9	2062	−7.0	7.6
KC	22914	13.3	82.5	10.6	43.5	80.7	2520	4.2	−6.0
KC 1	7884	9.6	84.4	9.7	44.3	78.2	2424	3.8	−6.2
KC 2	6206	17.6	82.7	10.8	45.4	83.4	2732	3.7	−5.9
KC 3	6056	13.4	80.1	10.0	43.7	80.9	2615	5.1	−6.2
KC 4	2768	14.0	82.3	13.6	37.3	81.0	2113	4.4	−5.5
SI	59971	5.5	84.8	13.2	38.5	91.6	2124	−7.8	6.1
SI 1	26596	5.9	85.6	14.8	35.9	93.1	2230	−7.3	6.3
SI 2	12880	5.5	82.4	14.1	38.2	91.8	2126	−9.9	6.0
SI 3	20495	5.1	85.6	10.6	42.0	89.5	1984	−7.3	5.9
SL	142297	15.8	81.6	18.4	32.4	85.0	2345	2.0	2.3
SL 1	32906	15.5	82.6	18.6	30.3	82.2	2457	1.4	2.0
SL 2	71972	15.5	81.6	18.2	33.3	87.1	2338	2.0	2.6
SL 3	6199	15.3	83.0	17.9	33.4	84.2	1278	1.9	2.4
SL 4	31220	17.0	80.2	18.8	32.3	83.4	2457	2.6	2.0

Table 1: Table of LHP and RHP type/subtype performance metrics and physical characteristics.

Interestingly, while each number of pitch subtypes is not the same per MLB Statcast pitch type, the total number of pitch subtypes ends up being 30 for both right-handed pitchers (RHP) and left-handed pitchers (LHP). We now consider varying levels of performance across the types and subtypes for each pitch. Since pitches could be successful in different manners, we choose different performance metrics: (i.) swinging strike percentage, (ii.) average exit velocity, and (iii.) extreme launch angles, which we define to be less than 0 degrees (ground ball) or greater than 40 degrees (pop fly). We first consider the aggregate performance of all pitches thrown in each subtype regardless of what other types of pitches are combined to form a pitch arsenal. Table 1 captures all 9 of the predominant pitch types for left-handed pitchers and right-handed pitchers on the left and right side of the table, respectively. Below each of the 9 types are the subtypes as defined by the aforementioned k-means clustering and elbow method. For the type and subtypes, we have presented the count of the total number of times each pitch has been thrown over the two seasons, the performance metrics, and the four physical dimensions over which we based the clustering.



(a) LHP break.

(b) LHP Spin/Velo.

(c) RHP break.

(d) RHP Spin/Velo.

Figure 1: Four physical dimensions for pitch subtype clustering separated into horizontal-vertical break (left) and spin-velocity (right) for left-handed (top) and right-handed (bottom) pitchers.

The performance of some subtypes can be vastly different, even for the same type of pitch. For example, RHP KC1 has a swinging strike percentage of only 9.6 percent as compared to an average of 13.3 and as high as 17.6 for KC2. The key distinction between KC1 and KC2 subtypes is that the lower-performing KC1 is 5.2 MPH slower but has a similar pitch shape in terms of horizontal and vertical break. To give a feel for another performance metric, we turn to the situation where the launch angle is above 40 degrees, producing a routine fly ball. For LHP, a high-spin splitter (FS3) produces a fly ball at a 30 percent rate versus 11.3 percent for a low-spin splitter (FS2). This relationship is flipped for changeups, where there is an advantage to reduced spin for increasing the ground ball rate (launch angle below 0 degrees). This can be seen in the low-spin version of the changeup (CH2 for both) versus a changeup with a higher spin (CH3 for both) with the RHP version increasing the ground ball rate by 13.8 percent.

We can more easily see the physical characteristics of spin in revolutions per minute (RPM) and the horizontal and vertical break in inches in Fig. 1, where we have separated the horizontal-vertical break into one graph and the spin and velocity into another graph. We observe that there is more horizontal-break diversity in subtype characteristics than vertical-break diversity. For example, while subtypes rarely span more than 1 or 2 vertical inches, they can have over 6 inches of difference in horizontal movement (*e.g.*, RHP FT). There is far greater distinction in the spin and velocity of subtypes, as observed by Fig. 1(b) and Fig. 1(d). For example, the cluster centers for sliders can vary by more than 1200 RPMs and over 7 MPH for changeups.

3 Evaluating the Effectiveness of Pitch Subtype Pairings

Our goal in this section is to quantify the effect of a single pitch subtype when the pitcher pairs that subtype with another subtype. To do so, we consider any time these reference subtypes are paired with each of the other subtypes, meaning the pitcher throws both subtypes. We evaluate all combinations of pitch pairings according to the same four performance metrics, as introduced in Section 2. In other words, we compare the aggregate performance of a pitch subtype (shown in Table 1) against the performance of that same pitch when paired with each of the 29 other subtypes to determine the most extreme gains and losses in performance. To do so, we create ordered lists for each of the performance metrics for each reference subtype when paired with all other subtypes, using a cutoff of at least 100 pitches thrown. Then, we identify the best subtype pair (Table 2) and worst subtype pair (Table 3) and show the difference (Δ) in performance from the reference of all occurrences of that subtype being thrown, presented in Table 1.

We now discuss some noteworthy observations from Table 2 and Table 3, going from top to bottom. We find that there is an interesting trend for the best changeup pairings based on different performance metrics. We find that the greatest swinging strike rate happens when there is a high level of distinction in at least one physical factor from the reference of a changeup, but distinct by handedness: LHP experience the best swinging strike pairings with subtypes that have the greatest horizontal separation from the changeup, whereas the greatest change in velocity is the key for RHP. Conversely, the biggest changes in exit velocity occur for both handedness when pitches are of similar break to changeups, inducing weak contact. What is striking with the poor pairings for changeups, especially for RHP, the FS that is most similar in break and velocity to the reference changeup subtype (see CH1 and FS3 and CH3 and FS1 in Table 1) dramatically reduces the swinging strike and ground ball rate outcomes of the changeup.

Sinkers (especially SI3) pair fairly universally well with curveballs, especially across performance metrics for LHP but even RHP. However, a lower-spin splitter (FS1) is the best match for all RHP

LHP Subtype	ΔSwK (%)		ΔExit Velo (MPH)		ΔLA>40° (Pop-up %)		ΔLA<0° (GB %)		RHP Subtype	ΔSwK (%)		ΔExit Velo (MPH)		ΔLA>40° (Pop-up %)		ΔLA<0° (GB %)	
CH1	FC3	1.3	FC2	−0.3	SI3	2.9	FC1	3.2	**CH1**	FC1	0.2	SI3	−0.5	SI1	1.8	SI2	2.1
CH2	KC4	1.9	SI3	−1.4	KC2	1.2	FS1	9.2	**CH2**	FS1	3.0	FS1	−1.6	FS1	2.6	SI2	3.8
CH3	FC2	1.8	FT2	−0.3	FF3	0.8	FC1	1.7	**CH3**	SI1	2.5	FS2	−2.3	FS1	14.6	KC2	4.6
CU1	FC2	0.7	SI3	−1.2	SI3	5.5	FF3	1.5	**CH4**	FF3	0.2	SI1	−0.7	CH3	0.8	SI3	1.2
CU2	SI3	1.2	SI3	−0.4	SL1	0.3	SI3	4.7	**CU1**	SI3	1.4	FS1	−0.7	FS1	2.4	KC2	12.1
CU3	SI3	4.2	SI3	−1.4	SI3	1.5	SL1	2.8	**CU2**	SI2	3.6	SI3	−1.6	FS1	3.9	KC4	10.7
FC1	KC3	2.8	SI3	−0.3	KC1	5.1	SI3	3.9	**CU3**	SI3	2.4	FS2	−0.9	FS1	4.4	FS2	4.9
FC2	SI2	1.9	FS1	−1.6	FS1	3.8	FS1	5.2	**FC1**	SL1	0.8	SL4	−0.5	FS3	7.4	SI2	1.3
FC3	SI3	1.4	SI3	−1.9	SI2	2.8	SL1	3.0	**FC2**	FT2	0.9	KC2	−1.8	FS3	1.9	FC3	1.3
FF1	FS2	0.8	FC3	−0.4	FS2	6.1	SI1	3.1	**FC3**	SL3	2.5	SL3	−0.4	KC1	2.1	SL3	1.4
FF2	SI3	1.0	SI3	−1.3	KC1	2.1	FS4	6.6	**FF1**	KC2	0.6	FS2	−0.4	FC1	1.1	SI2	2.1
FF3	FS2	1.6	KC2	−0.4	FS2	6.0	SI3	1.1	**FF2**	SI1	0.6	SI1	−0.5	FS1	2.6	SI2	4.1
FS1	FC3	2.5	SL4	−3.1	SL4	10.9	SL3	0.7	**FF3**	KC4	0.8	SI3	−0.3	FS2	1.6	SI2	3.5
FS2	CU3	0.4	SL3	−1.5	SL3	2.3	FS4	0.5	**FS1**	CH1	1.5	CH1	−1.6	KC3	4.0	SI2	8.1
FS3	FT1	0.4	CU3	−6.0	FT2	1.6	FS1	0.2	**FS2**	CH2	1.4	CH3	−0.7	CH4	2.7	SI2	6.8
FS4	CH2	2.8	CU3	−1.6	CU2	3.8	CH2	2.7	**FS3**	SI2	3.1	SI2	−1.4	CH3	3.4	SI1	7.9
FT1	FS1	0.7	KC1	−1.2	KC1	5.6	SI2	3.5	**FT1**	SI2	0.3	SI1	−0.2	KC2	2.0	FS2	4.3
FT2	CU2	0.4	KC3	−1.2	KC1	9.2	SI1	4.7	**FT2**	SI2	1.2	FS1	−1.4	SI2	6.1	KC3	1.6
FT3	SI3	3.2	SI3	−1.2	KC1	4.7	SL4	3.0	**FT3**	FS3	0.6	CH3	−0.2	KC1	0.7	FC1	1.9
KC1	SL3	2.4	CH3	−0.1	FT3	1.7	FC2	4.8	**KC1**	FS3	3.3	SI3	−2.4	FC3	3.0	CU2	3.3
KC2	SL2	3.3	FT3	−0.7	SL2	3.2	FC2	3.5	**KC2**	FC2	3.1	SL4	−1.3	SL4	2.8	FC3	4.0
KC3	SL2	0.5	SL2	−0.8	SL2	1.6	FT1	1.5	**KC3**	FC3	0.8	SI1	−2.2	SI1	2.2	CU2	5.4
KC4	KC2	1.6	KC2	−1.0	SI3	6.6	KC2	5.1	**KC4**	KC2	1.3	KC2	−0.9	FS3	4.8	CU2	5.4
SI1	CU2	0.6	KC2	−0.6	FC2	8.8	FT2	7.9	**SI1**	FS3	2.0	FT3	−1.7	FT3	3.1	KC1	3.5
SI2	FF1	1.5	FT1	−1.5	CU1	5.9	FC3	6.1	**SI2**	SL4	0.3	FT3	−0.7	FS1	3.9	KC1	4.0
SI3	FF1	0.4	FF3	−1.5	CU1	5.5	FC2	13.0	**SI3**	FT2	0.8	FF3	−0.6	FS1	3.6	KC4	4.5
SL1	FS2	1.2	FS4	−3.3	FS4	2.8	FS3	4.9	**SL1**	KC2	2.3	SI2	−1.8	KC4	2.8	KC2	7.3
SL2	SI2	0.9	KC1	−1.5	SI3	6.8	FC2	3.2	**SL2**	SI1	0.9	SI2	−0.8	FS2	3.3	FF3	0.1
SL3	FC2	0.7	FS4	−1.0	CU3	2.7	FC1	4.3	**SL3**	KC1	2.9	SI3	−2.2	KC1	3.9	FS3	4.6
SL4	FS1	1.2	CU3	−0.9	FS3	0.9	CU1	4.8	**SL4**	KC2	4.3	SI2	−0.8	FS1	4.0	KC2	2.8
AVG. GAIN		1.5		−1.3		4.1		4.0	**AVG. GAIN**		1.7		−1.1		3.5		4.3

Table 2: Best subtype pairings in terms of gain in each of the three performance metrics for the reference subtype for LHP (left) and RHP (right).

curveball types for pop-up percentage and the more downward knuckle curve dramatically helps the CU to induce more ground balls. In fact, SI can pair well and poorly with FS and driven by the velocity separation, since they have very similar movement and can have large spin differences with poor pairings.

For cutters (FC) and splitters (FS), we see a compelling opposite trend. Namely, cutters play up (Table 2) when they are paired with pitches with more positive horizontal break and play down (Table 3) with pitches with more negative horizontal break. Conversely, RHP splitters play up when they are paired with pitches with more negative horizontal break and play down when paired with pitches with more positive horizontal break. LHP cutters play up with pitches with more negative horizontal break, such as sinkers for swinging strike rate and exit velocity. When SL2 or SL3 is paired with the cutter, the differing horizontal and vertical break induces more ground balls. When SL1 or SL4 is matched with the curveball (SL1 and CU2 and SL4 and CU1) both losses occur of swinging strike rate going down and stronger contact being induced. The poor pairings seemingly result from differing vertical break between the pitch subtypes.

Both fastball (FF and FT) subtypes seem to be the least affected by the pairings in terms of swinging strike differences (1.6Δ). Notice though that high-spin FF pairs better with low-spin KC (and better velocity separation) versus low-spin FF with high spin KC. Also, notice that the highest speed, highest spin class of FT pairs best with SI and worst with the slowest changeups. With

LHP Subtype	ΔSwK (%)		ΔExit Velo (MPH)		ΔLA>40° (Pop-up %)		ΔLA<0° (GB %)		RHP Subtype	ΔSwK (%)		ΔExit Velo (MPH)		ΔLA>40° (Pop-up %)		ΔLA<0° (GB %)	
CH1	SI2	−2.1	SI1	0.5	FC1	−1.9	SI2	−2.2	**CH1**	FS3	−3.2	FS2	1.9	FC3	−1.2	FS3	−6.8
CH2	CU3	−0.6	FS1	2.7	SI2	−2.6	CU2	−1.6	**CH2**	KC3	−0.7	CU2	0.4	SI2	−1.7	FS2	−2.5
CH3	KC4	−1.0	KC4	1.3	KC4	−3.0	KC2	−2.0	**CH3**	FS1	−2.6	KC3	2.0	KC1	−4.4	FS1	−11.0
CU1	SL3	−0.4	SL3	1.0	FC1	−2.8	SL4	−4.0	**CH4**	KC4	−2.0	KC1	1.1	KC2	−2.8	CH3	−1.1
CU2	SL3	−0.6	FC1	0.9	SI1	−1.7	FC3	−1.0	**CU1**	FS1	−2.3	KC2	3.1	KC2	−4.5	FS1	−6.0
CU3	SL1	−2.2	FC1	0.8	FT1	−1.3	SI2	−5.4	**CU2**	FS1	−4.0	SL4	0.5	KC4	−7.2	FS1	−6.5
FC1	CU3	−1.2	SL3	1.0	SI3	−1.2	KC1	−6.1	**CU3**	SL4	−1.2	KC4	1.6	KC4	−1.6	SI2	−3.5
FC2	FS1	−2.5	FF3	0.2	FF3	−0.2	SI1	−3.3	**FC1**	CH3	−1.6	CH3	0.7	CH3	−1.0	FS3	−7.6
FC3	SL3	−2.3	KC3	1.6	SL1	−2.0	CU1	−1.5	**FC2**	SI3	−1.9	FS3	2.1	SI3	−1.7	FS3	−3.8
FF1	SI2	−0.9	FS1	0.7	SI2	−3.4	FS2	−6.5	**FC3**	FS3	−3.5	FT2	0.3	SI3	−1.5	KC2	−3.4
FF2	KC4	−0.7	KC1	2.9	FS4	−5.3	FS3	−2.6	**FF1**	SI2	−0.9	KC1	0.3	SI2	−3.0	FS2	−1.7
FF3	SI3	−2.7	FS4	1.9	SI3	−5.1	FS2	−3.1	**FF2**	KC3	−0.9	KC2	0.5	SI2	−3.8	FS1	−1.5
FS1	SL1	−2.2	CU3	1.4	CU3	−7.0	SL4	−4.6	**FF3**	CU2	−0.4	FS1	0.3	SI1	−1.8	CH3	−1.1
FS2	SL1	−1.8	FC2	0.3	CU2	−0.8	SL1	−1.5	**FS1**	SI2	−2.3	FC1	2.4	SI2	−4.6	KC3	−7.4
FS3	FF2	−0.1	SL4	1.0	CU3	−6.2	FT1	−1.8	**FS2**	FC2	−2.6	CU3	0.9	SI2	−2.3	CH4	−4.3
FS4	FT3	−2.0	CH1	2.2	CH2	−7.4	FT1	−2.7	**FS3**	CH3	−3.6	KC1	2.3	KC4	−3.2	CH3	−4.7
FT1	SI1	−1.7	CU3	0.5	SI2	−1.7	KC2	−6.7	**FT1**	SI3	−0.6	KC1	1.3	SI3	−1.9	KC2	−4.5
FT2	KC2	−1.3	FC3	0.5	SL4	−1.8	KC2	−11.8	**FT2**	CH3	−0.6	SI2	2.5	CH4	−0.9	SI2	−10.3
FT3	CU3	−1.1	FC2	0.5	SL4	−1.5	KC1	−10.7	**FT3**	SI3	−0.9	KC3	1.0	FS2	−1.8	KC1	−4.4
KC1	FT3	−1.6	FC2	1.2	FC2	−4.0	FT3	−5.8	**KC1**	SI2	−2.1	FC3	0.3	CU2	−5.7	CU1	−6.5
KC2	FT3	−1.3	KC4	0.4	KC4	−1.6	FT3	−5.3	**KC2**	SI2	−6.4	SI2	1.0	CH3	−1.2	CU3	−5.0
KC3	FT2	−0.4	FT1	0.7	FT1	−0.7	SL2	−1.5	**KC3**	SL1	−3.0	CU1	1.3	CU2	−3.1	SI3	−5.1
KC4	SL4	−4.1	SI2	1.8	FC3	−3.6	SI3	−10.9	**KC4**	SL3	−3.5	SL3	1.2	CU2	−4.7	SL3	−9.2
SI1	KC1	−2.0	FC1	0.8	FT2	−5.5	FC2	−6.8	**SI1**	KC1	−1.0	CH3	0.8	KC1	−1.3	FS1	−5.0
SI2	CU3	−1.3	FC2	2.5	FC3	−2.9	CU3	−10.8	**SI2**	FS3	−1.3	FS1	1.6	KC1	−2.8	FS1	−6.3
SI3	FC1	−1.2	SL4	0.5	FT2	−5.2	CU1	−9.9	**SI3**	FS1	−1.2	FS2	0.9	KC1	−1.7	FS1	−7.0
SL1	FC2	−2.4	FC2	1.2	FS3	−4.2	CU1	−3.7	**SL1**	FS1	−3.2	FC2	0.5	KC2	−5.8	CU1	−1.4
SL2	FC3	−4.0	CU3	0.5	FC2	−1.9	KC1	−3.2	**SL2**	KC1	−2.3	FS1	0.6	KC1	−0.9	SI2	−2.5
SL3	FS4	−3.9	CU3	0.8	FS4	−3.3	CU3	−4.1	**SL3**	CU3	−1.4	FT2	0.4	FC2	−2.9	CH1	−0.5
SL4	FC1	−2.0	FC1	1.2	CU1	−1.3	FC3	−4.3	**SL4**	CU3	−1.0	KC1	1.7	FC2	−0.6	FS1	−4.7
AVG. LOSS		−1.7		1.1		−3.0		−4.8	**AVG. LOSS**		−2.1		1.2		−2.7		−4.8

Table 3: Worst subtype pairings in terms of loss in each of the three performance metrics for the reference subtype for LHP (left) and RHP (right).

lefties, SI2 or SI3 is paired well with FF2 or FF3 with respect to swinging strike rate. Four-seam fastballs pair poorly with splitters with regards to failing to induce ground balls (significant spin difference and vertical break change).

For RHP, knuckle curves can have very positive pairings with FS (similar velocity but very different vertical and horizontal movement) and FC (similar horizontal movement but substantial speed difference and vertical action). However, from Table 3, we find that KC pairs poorly with SI (dissimilar speed and dissimilar movement in both directions) and SL (similar speed and most similar movement other than CU) for RHP. Unlike for RHP, the KC and SL2 or KC and SL3 is a positive pairing (very different vertical movement) for swinging strike rate for LHP. For LHP, KC and FT has a negative pairing (very different horizontal and vertical movement and very different velocity) and plays down for swinging strike rate and ground ball rate.

For RHP, slider subtypes have various KC subtypes that pair well for increasing swinging strike rate and increasing ground and fly balls, whereas SI2 and SI3 reduce exit velocity. For LHP, sliders when paired with cutters, especially FC2 or FC3, seemed to reduce swinging strike rate and induce harder contact.

To accentuate the value of this pitch pairing research there are a couple of examples of one pitch in isolation having different performance than when paired with others. One example of a mediocre pitch having profound pairing impact is RHP SI2, which has only a 5.5 percent swinging strike rate and a decent ground ball rate (38.2). However, there are 17 instances where SI2 helps another subtype to have improved performance. For example, SI2 greatly helps slider with reducing hard contact. Conversely, RHP FS1 with low speed and low spin is somewhat of a black hole of pitch pairing, having 16 instances where it worsens the performance of a subtype.

4 Extremes in Pairing Frequency and Pitcher Performance Level

In this section, we consider some extremes when it comes to overall and pitch type quality as well as specific major league pitcher subtype pairs. Even pitchers that don't seem to be standouts in terms of overall quality – as judged by a league-adjusted statistic like ERA+ – most often get plenty of value from optimal pitch subtype pairing.

For right-handed starters: The beneficial CU1 and SI3 and CU3 and SI3 pairings were thrown by Aaron Nola, Adam Wainwright, Felix Hernandez, Scott Feldman, Mike Pelfrey, and Kyle Hendricks. Hendricks had an ERA+ of 170, and Nola's CU1 had a 17.72% swinging strike rate, 7.05% higher than the average CU1, and his CU3 had 20.35% swinging strike rate, 8.06% higher than that subtype by itself. While Pelfrey and Wainwright don't stand out overall, their curveballs as typed by Baseball Prospectus both had above-average whiff and grounder rates in 2017.

The CU2 and SI2 pairing was notably thrown by Corey Kluber (ERA+ 167) and Zack Godley (106). Kluber had a 26.16% swinging strike rate for his CU2, 13.88% higher than CU2 by itself. The CH2 and FS1 and CH3 and FS1 pairings, which we showed to increase pop-up rate, was thrown most by Matt Shoemaker (100) and Tyler Clippard (107), both pitchers that were in the top quartile when it came to pop-up rate – with only two pitchers (minimum 100 innings pitched in 2016 and 2017 combined) having a higher pop-up rate than Clippard.

Jeff Samardzija (101) threw the most of the CU2 and KC4 pairing or the CU3 and KC4 as well as the poor pairing of KC4 and SL3. A poor pairing - curves and FS1 – was thrown most often by Samardzija (101) and Jason Hammel (94). Samardzija's CU1 swinging strike rate was 7.32%, or 3.35% worse than CU1 overall when paired with FS1, and in a related matter, the pitcher had mostly stopped throwing any curves by 2019.

Alex Cobb (101) employed the KC1 and FS3 combination the most – only two pitch subtype pairings were more beneficial by swinging strike rate. The solid KC2 and FC2 pairing and the nearby KC3 and FC3 pairing appear to be best utilized by closers, especially Wade Davis (207) and Mark Melancon (171). Wade Davis's KC2 had a swinging strike rate of 20.86%, 3.25% higher than KC2 overall. Also, Trevor Bauer (107), James Shields (74), and Mike Leake (96) frequently threw these pairings. The poor KC1 and SI2 and KC2 and SI2 pairings were thrown most frequently by Jarred Cosart (72), Edinson Volquez (84), Trevor Cahill (107), and Leake (96).

The SL1, SL2, or SL4 all made good pairs with SI2, especially when you considered their ability to reduce exit velocity. Those pairings were thrown the most by Cory Gearrin (142), Jimmy Nelson (107), Joe Ross (107), Jake Junis (104), and Leake (96). Gearrin's SL1, SL2, and SL4 had average exit velocities of about 3.5 mph lower than sliders overall.

For lefties, the CH3 and FC2 pairing (good for swinging strike rate) was thrown the most by Cole Hamels (126), Hyun-Jin Ryu (102), Mike Montgomery (142), David Price (117), and Justin Nicolino (79). Cole Hamels's CH3 has a swinging strike rate of 24.44%, 8.99% more than CH3 overall. The bad CH3 and KC4 pairing was thrown the most by Alex Wood (137), Matt Moore (87), and David Price (117).

The good CU2 and SI3 and CU3 and SI3 pairings were utilized most often by Jon Lester (128), Steven Matz (94), Jerry Blevins (143), and Buddy Boshers (95). Lester's CU2 had a swinging strike rate of 28.26%, which was 15.04% more than all CU2 overall. Jerry Blevins's CU3 had a swinging strike rate of 25.82%, or 13.81% more than all CU3 overall. Lester (128) and Chris Rusin (155) led the way with the beneficial FC3 and SI3 pairing.

Despite having relative success overall by ERA+, Jason Vargas (111), Sammy Solis (117), and David Price (117) threw the most of the KC1 and FT3 and KC2 and FT3 pairings. David Price's KC2 had a swinging strike rate of 5.26%, which was 5.11% lower than all KC2. The successful SI2 and FF1 pairing was thrown the most by Lester (128) and CC Sabathia (115). Richard Bleier (220) threw the most of the SI3 and FC2 pairing, which is very good for ground balls.

Drew Smyly (82) and Dallas Keuchel (105) threw the most of SL1 and FC2 (bad for swinging strike rate and bad for inducing weak contact). Drew Smyly's SL1 has a swinging strike rate of 13.28%, or 2.87% lower than all sliders. Dallas Keuchel's SL1 has an exit velocity of 86.32 mph, 5.57 mph more than all SL1 for pitchers who also throw FC2.

5 Conclusion

In this paper, we used k-means clustering and the elbow method to classify pitch subtypes from previously-labeled MLB Statcast pitch types. In doing so, we understood the degree to which subtypes differ across a type and evaluated the effectiveness of pairing subtypes. Between the best and worst pairing of subtypes, we found that there is an average change of 3.5 percent swinging strike rate, a 2.4 MPH exit velocity, 3.3 percent pop-up rate, and 4.5 percent ground ball rate. Lastly, based on frequency of the best and worst pairings, we showed examples of pitchers and discussed their level of performance. We hope that this work leads to intuition on where to focus efforts with pitcher scouting, pitch design, and player development.

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